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TITLE: IMPACT OF THE ADOPTION OF ARTIFICIAL INTELLIGENCE ON THE STRUCTURE OF EUROPEAN EMPLOYMENT (2023-2024): AN EMPIRICAL ANALYSIS BY SECTORS AND OCCUPATIONS

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SUMMARY AND KEYWORDS

This paper empirically analyses the impact of the adoption of artificial intelligence (AI) on the structure of employment in Europe during 2023-2024, with an approach disaggregated by economic sectors and occupations. Based on recently available Eurostat data, a data dashboard is constructed for multiple European countries, integrating information on the proportion of companies using AI and the distribution of employment by sectors (NACE Rev.2) and occupations (ISCO-08). Using econometric models of fixed-effect panel data, we examine whether greater enterprise adoption of AI is associated with changes in the relative share of employment across sectors and occupational categories.

The results indicate that the adoption of AI has heterogeneous effects, where a relative increase in employment is observed in knowledge-intensive sectors (e.g. professional and technological services) and decreases in low-skilled sectors or with routine tasks (such as commerce or transport). Similarly, at the occupational level, high-skilled occupations, intensive in advanced cognitive tasks, increase their relative weight in employment under higher levels of AI adoption, while lower-skilled or more routine occupations tend to reduce their relative participation. These trends suggest that, in the recent European context, AI could be acting more as a complement to skilled work and a partial substitute in routine positions. However, the formal econometric analysis using a routine intensity index does not find conclusive evidence of differential effects according to the content of tasks, probably due to the short time horizon considered, while the econometric analysis disaggregated by sub-tasks showed an association of complementarity in routine manual tasks, contradicting classical theories. Overall, the study provides initial evidence on how the emergence of AI reconfigures the structure of employment, and discusses policy implications aimed at facilitating the adaptation of the workforce to this technological transition.

Keywords: Artificial intelligence, labour market, automation, European employment, technological adoption, routine tasks, job qualification, labour structure

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1. INTRODUCTION

The rapid emergence of artificial intelligence (AI) in the contemporary economy has created uncertainty about the future of the labour market in the face of technological progress. Historically, automation had a heterogeneous substitution effect on employment, depending on the type of tasks that could be replaced by machinery. However, technological progress also led to the creation of new tasks, increasing the demand for work in other areas and causing structural shifts in the structure of employment, avoiding permanent mass unemployment. The question then arises: Will artificial intelligence follow a pattern similar to that of the technological advances of the past?

In recent years, new advances have emerged in AI-related technologies, characterized by their advanced cognitive capabilities, such as data-driven learning (Machine Learning) and deep neural networks (Deep Learning). The current focus is on the latest trend in technology, Generative AI, a branch of AI focused on the creation of original content (text, images, etc.) from existing data using deep learning models. The impact of the new generation of AI in the short and long term is a topic of current debate, as a significant effect is anticipated not only at the macroeconomic level, but also at the individual level.

In this context, the main objective of this Final Degree Project is to empirically analyse how the adoption of AI technologies by companies is affecting the structure of employment in Europe in recent years. In particular, this impact will be studied by differentiating by branches of economic activity (NACE Rev. 2 classification) and by occupational groups (ISCO-08 classification) during 2023 and 2024. In this way, the work explores the heterogeneity of the impact of AI at different levels, something that is still little addressed in the literature.

The main hypothesis is that the adoption of AI will have a heterogeneous effect on employment according to the type of predominant tasks. Specifically, inspired by the theoretical framework of routine vs. non-routine tasks, it is expected that in sectors intensive in routine tasks (mechanical or repetitive) the diffusion of AI will be associated with reductions in the participation of these sectors in total employment (indicating possible technological substitution effects). Conversely, in non-routine-intensive sectors (which often require advanced cognitive or creative skills) AI would act more as a complement to human labor, with a higher share of employment expected in such sectors under high levels of AI adoption. A similar pattern is also anticipated at the occupational level, where highly skilled occupations (intensive in non-routine, cognitive tasks) could benefit from or better resist AI automation, while low-skilled or routine-intensive occupations would be the most susceptible to displacement or relative weight loss.

To test this hypothesis, the study uses econometric models of panel data with fixed effects by country-sector (or country-occupational group) and year, using indicators of AI adoption at the sectoral level and measuring the evolution of employment composition. In methodological terms, it is controlled for relevant macroeconomic factors, such as GDP per capita, the educational level of the labor force, or the unemployment rate, in order to isolate, as far as possible with aggregated data, the specific association between AI diffusion and employment structure.

The structure of this paper is as follows: Section 2 presents an exhaustive review of the existing literature and identifies relevant gaps in the research. Section 3 describes in detail the data used and the econometric methodology used. Section 4 provides a preliminary descriptive analysis of the data that anticipates the main patterns observed. The main results of the econometric analysis are presented and discussed in Section 5, while Section 6 assesses the fit of these findings with standard macroeconomic models. Additional tests to verify the robustness of the results are detailed in Section 7. Section 8 provides a comprehensive discussion of the economic and political implications, and finally, in Section 9, general conclusions are offered, limitations of the study are identified, and future lines of research are suggested.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. The impact of AI and automation on employment

The growing adoption of artificial intelligence and automation technologies has generated an intense debate around their impact on the labor market. The literature shows different positions on whether these technologies destroy or create jobs, highlighting both negative and positive effects depending on tasks and contexts.

Frey and Osborne (2013) analyzed the vulnerability of different occupations to automation and estimated that about 47% of jobs in the United States were at high risk of being automated in the coming decades, especially those associated with routine and repetitive tasks. This study became a benchmark for identifying the job profiles most exposed to advanced technologies.

Acemoglu and Restrepo (2020) empirically evaluated the introduction of industrial robots into the U.S. labor market. Their results showed that, for every additional robot per thousand workers, the employment rate falls and average wages fall, evidencing displacing effects of automation in certain regions and manufacturing sectors.

On the other hand, the Organisation for Economic Co-operation and Development (OECD, 2019) stresses that the net impact of automation depends to a large extent on the ability of workers and training systems to adapt. The report highlights that investment in training and professional retraining is crucial for the workforce to transition to the new positions that emerge in the digital economy.

Therefore, studies indicate that AI and automation have a significant effect on employment, but the magnitude and direction of this effect varies according to the type of tasks performed and the institutional response in terms of training. The following sections start from this debate and analyse how the theory of routine and non-routine tasks explains these heterogeneous effects on the structure of employment.

2.2. Theory of routine and non-routine tasks

The theory of routine and non-routine tasks says that the impact of new technologies varies according to the nature of the work tasks. Generally speaking, routine tasks (those that are repetitive, predictable, and codifiable) are highly susceptible to being automated, while non-routine tasks (that require creative thinking, complex problem-solving, or interpersonal interaction) tend to be supplemented by technology rather than replaced.

Autor, Levy and Murnane (2003) formalized this theoretical framework by demonstrating that computerization was associated with a lower demand for work in routine tasks (manual and cognitive) and an increase in the demand for work in non-routine tasks of a cognitive nature. In other words, computers replace repetitive routine activities, but boost workers' productivity in complex non-routine tasks.

This task-focused approach has been instrumental in explaining the employment polarization observed in recent decades. For example, Autor and Dorn (2013) documented in the United States a decrease in medium-skilled jobs intensive in routine tasks, accompanied by a relative growth of occupations at the high and low ends of the distribution of skills, i.e., cognitive non-routine jobs (professional, technical) and also certain non-routine manual service jobs. while routine administrative or manufacturing jobs contracted. European studies found similar patterns of job displacement from routine to non-routine occupations in services and knowledge sectors (Goos, Manning, & Salomons, 2014).

For analytical purposes, metrics have been developed to quantify the routine content of each occupation. The Routine Task Intensity (RTI) index stands out, which synthesizes what fraction of the tasks in an occupation are routine in nature. High RTI values indicate highly automatable occupations, while low values reflect a higher proportion of non-routine tasks. In addition, recent studies such as that of Mihaylov and Tijdens (2019), construct routine and non-routine content indices for 427 detailed occupations (4-digit, ISCO-08), providing an empirical basis to compare how different occupations might be affected by automation.

In summary, the theory of routine and non-routine tasks offers conceptual support to understand the heterogeneous effects of technological progress, where a substitution of human work in routine tasks and a complementation in non-routine tasks is anticipated, theories that will be tested in later sections.

2.3. Recent empirical evidence on AI and employment

The empirical evidence on the impact of AI on employment is still uncertain and with mixed results, depending on the geographical context and methodological approach. In the case of Europe, recent studies suggest positive or complementary effects on high-skilled occupations. For example, an analysis in 16 European countries by Albanesi et al. (2023) identified that occupations with higher exposure to AI technologies have increased their share of total employment. This increase was particularly seen in occupations characterized by a younger, highly educated workforce, indicating that AI adoption has tended to complement skilled workers rather than replace them. Therefore, until 2022, AI in Europe was associated with higher demand for work in knowledge-intensive occupations.

In contrast, evidence from the United States suggests that AI can have disruptive effects on lower-skill jobs. A study by Bonfiglioli et al. (2023) looked at the early spread of AI in U.S. commuting zones during 2000-2020. Their results indicated that AI adoption was associated with a net reduction in employment, except in higher-paid occupations or those requiring STEM (Science, Technology, Engineering and Mathematics) training, in other words, in the regions most exposed to AI, employment decreased in aggregate terms, except in highly skilled positions, that would have resisted or even prospered. These findings suggest that, at least in the initial phase analyzed, AI primarily acted as a substitute for labor in many occupations, mitigating its negative impact only on high-skilled roles.

Beyond these specific studies, estimates on AI and employment vary depending on the approach. Some research and influential voices highlight the opportunities that AI creates.

For example, Brynjolfsson et al. (2018) argue that AI can increase worker productivity by taking on routine tasks, freeing up employees to focus on higher value-added functions. Along these optimistic lines, it has been estimated that AI will generate as many new jobs (in areas of development, maintenance and use of these technologies) as it could displace. On the contrary, other experts highlight the risks, where Acemoglu (2022) warns that, if adequate policies are not implemented, companies could use AI mainly to automate processes instead of complementing them, reducing the demand for workers. Similarly, Acemoglu and Johnson (2023) stress that the benefits of AI could be concentrated in certain economic elites if its development is not channelled towards widespread improvements in shared productivity.

In summary, recent evidence suggests that the impact of AI on employment is not uniform, but depends on the type of tasks that predominate in each sector or occupation, as well as the institutional and temporal context analyzed. In Europe, for now, there are predominant indications that AI complements skilled workers (rather than massively destroying jobs), while in other environments and work segments substitution effects have been detected. This diversity of results emphasizes continuing to investigate the AI-employment relationship with different approaches and more current data, to understand under what conditions AI acts as a complement or substitute for human work.

2.4. Research gaps and motivation of this study

Despite the growing number of studies on AI and automation, there are research gaps in the understanding of their labor effects, which directly motivates the present work.

First, much of the literature to date has been based on theoretical projections or analyses of previous technological waves (industrial robots, computerization of the 2000s) rather than empirical data from the current generation of AI. This leaves it uncertain whether modern AI, especially generative AI that emerged in 2022-2023, will follow the same pattern as previous technologies. Indeed, while historical experience suggests that fears of technological unemployment are often exaggerated (past innovations eventually generated new opportunities), it remains an unknown whether AI will adopt this pattern or, on the contrary, could have unprecedented effects on the labor market.

One specific gap comes from the lack of recent data on AI adoption. Many studies relied on proxy indicators (such as the number of AI patents, expert assessments of what tasks AI can do) rather than observed data on AI use in companies. This means that we don't know for sure how the actual adoption of AI by companies is affecting different industries and occupations in the present tense.

Another gap relates to causal identification and context heterogeneity. Since AI adoption often correlates with other trends (e.g., the overall digital transformation of a company or country), it is difficult to isolate AI's own effect on employment. Many macro studies face challenges in distinguishing correlation from causation and more detailed approximations are needed, something that aggregate data does not readily allow. In addition, most of the available evidence comes from the US or other settings, while Europe has different labour institutions and sectoral structures that could moderate the impact of AI. This suggests the importance of studying the European case with one's own data, rather than extrapolating foreign conclusions.

The motivation of this Final Degree Project lies in contributing to filling these gaps. Drawing on very recent European data (2023-2024), the study offers one of the first empirical assessments of how AI adoption relates to the distribution of employment by sectors and occupations in Europe. Unlike previous analyses, which are usually forward-looking or from earlier periods, this research directly looks at the initial phase of diffusion of generative AI and other AI technologies in companies. Likewise, when disaggregated by branches of activity and occupational groups, the study explores the heterogeneity of the impact in a way that has been little addressed so far in the literature. With this, this work aims to provide objective evidence to the debate, informing whether in the recent European context AI associates more of a complementary role to human work or substitution, and laying the foundations for future more in-depth research.

3. DATA AND METHODOLOGY

To answer our research question, a panel database was constructed by combining information from Eurostat for 29 European countries[1] during the years 2023-2024.

The main independent variable is the adoption of Artificial Intelligence (AI) by companies. This information comes from Eurostat's annual survey on the use of information and communication technologies (ICT) in enterprises (Digital Economy and Society), which provides data based on independent samples selected through stratified random sampling for each year and country. From this source, indicators were used[2] regarding the percentage of companies that declare using some AI technology, differentiated according to economic activity, country and year. For our analysis, we aggregate this data at the sector-country-year level within the `IA_Adoption` variable, defined as the percentage of companies in each sector, country, and year that use AI-based technologies.

The dependent variable is defined as the relative share of employment in each economic sector (NACE Rev. 2 classification[3]) and occupational group (ISCO-08 classification[4]). These data come from the Labour Force Survey (EU-LFS) compiled by Eurostat.

In the sectoral model, the dependent variable is the proportion of total employment in each economic sector called `Share_Sector`, according to the NACE Rev.2 classification. In the occupational model, the dependent variable corresponds to the proportion of employment in each occupational group within each economic sector and is called `Share_Occupation`, according to the ISCO-08 classification. These proportions were obtained using aggregate tables provided by Eurostat, which allow the relative weight of each sector and occupation to be consistently compared, eliminating distortions derived from the differential economic size between countries.

To isolate as far as possible the association between AI adoption and the aggregate structure of employment, relevant macroeconomic variables were introduced, also extracted from Eurostat, aggregated by country and year:

- Real GDP per capita (`GDPCap`): GDP adjusted for purchasing power parity, including to control for differences in the business cycle or level of development between countries.
- Educational level (`Educ_Rate`): Proportion of employed people between 25 and 64 years of age with tertiary education (ISCED 2011), to capture differences in the educational structure of the countries.
- Unemployment rate (`Unemp_Rate`): The percentage of the active population that is unemployed, controlling for structural differences in the labour market.

[1] Table A14 (Annex). Full list of countries and number of observations per country
[2] Table A6 (Annex). AI adoption indicators: Eurostat codes and description
[3] Table A15 (Annex). Detailed 1-digit NACE Rev.2 classification
[4] Table A5 (Annex). Detailed ISCO-08 classification by major groups (0C0-0C9)

The econometric methodology used are panel data models with fixed effects by country and year, estimated using Ordinary Least Squares (OLS). With this specification, each country has its own constant term (country fixed effect), and each year also has a temporary fixed effect. This makes it possible to control for constant unobservable characteristics of each country (institutional, cultural or structural factors) and temporary shocks common to all countries. Thus, the results reflect only intra-country variations in the sectoral adoption of AI and its association with the aggregate structure of employment.

Additionally, to correct potential heteroskedasticity and autocorrelation problems, robust standard errors clustered by country in the sectoral model and by country-sector-year in the occupational model were used, since the ten occupations within each cell share the same exposure to AI and the same macro conditions. This produces robust standard errors guaranteeing valid statistical inferences.

3.1. Sectoral model (NACE Rev. 2 classification)

The first model estimates the sectoral effect of AI adoption on the relative share of employment:

$$Share\_Sector_{i,s,t} = \beta_0 + \beta_1 \times IA\_Adoption_{i,s,t} + \beta_2 \times GDPCap_{i,t} + \beta_3 \times Educ\_Rate_{i,t} + \beta_4 \times Unemp\_Rate_{i,t} + \sum_{s \neq M} \gamma_s \left[Sector_s \times IA\_Adoption_{i,s,t}\right] + \mu_i + \lambda_t + \varepsilon_{i,s,t}$$

Where:

- i = country
- s = economic sector (NACE Rev. 2 classification; section M is taken as the base category, so the sum excludes s=M)
- t = year
- μi = country-fixed effects
- λt = fixed effects of time
- $\varepsilon_{i,s,t}$ = idiosyncratic error term

This model incorporates interactions between AI adoption (`IA_Adoption`) and economic sectors according to the NACE Rev. 2 classification, based on sector M (professional, scientific and technical activities). The coefficient β1 indicates the average effect of AI adoption on the employment share in this base sector, while the coefficients γs indicate the differential effects of AI in other sectors with respect to the base category.

3.2. Occupational model (ISCO-08 classification)

The second model estimates how the occupational composition of employment varies between sectors with different levels of AI adoption. The econometric specification is as follows:

$$Share\_Occupation_{i,s,o,t} = \beta_0 + \beta_1 \times IA\_Adoption_{i,s,t} + \beta_2 \times GDPCap_{i,t} + \beta_3 \times Educ\_Rate_{i,t} + \beta_4 \times Unemp\_Rate_{i,t} + \sum_{o \neq OC2} \gamma_o \left[Occupation_o \times IA\_Adoption_{i,s,t}\right] + \sum_s \delta_s [Sector_s] + \mu_i + \lambda_t + \varepsilon_{i,s,o,t}$$

Where:

- i = country
- o = occupation (ISCO-08 classification; the OC2 group is taken as the base category, so the sum excludes o=OC2)
- t = year
- μi = country-fixed effects
- λt = fixed effects of time
- $\varepsilon_{i,s,t}$ = idiosyncratic error term

This model includes the interaction between AI adoption and the occupational groups defined according to ISCO-08, using OC2 (Scientific and Intellectual Professionals) as a base category. The $\beta 1$ coefficient measures the estimated average effect of AI adoption on the baseline group employment share (CO2), while the γo coefficients capture the estimated differential effects for each occupational group with respect to the base group. In addition, sectoral dummy variables (δs) are introduced to control for constant structural differences between economic sectors.

The IA_Adoption variable, as it is aggregated by sector-country-year, is identical for all occupations within the same sector-country-year. Therefore, the model estimates how the occupational distribution of employment varies between sectors and countries according to their degree of sectoral penetration of AI, controlling for national and temporal fixed effects.

To correct possible problems of heteroskedasticity and correlation of errors within each sector-country-year, robust standard errors clustered at this cluster level are estimated.

3.3. Final methodological comment

The total effect of AI adoption in each sector or occupation is obtained by adding the estimated coefficient for the IA_Adoption variable (representing the base category) and the coefficient corresponding to the specific interaction of each sector or occupation. From this linear combination, standard errors and p-values are also calculated, thus allowing the significance of the differential effect of AI on relative employment in each economic sector to be statistically evaluated.

In the sectoral and occupational model, the main study variable is aggregated by sector-country-year, and country-year for the control variables, therefore, the results obtained should be interpreted with caution, as statistical associations at the aggregate level, and not as individual or direct causal effects.

Sectoral adoption of AI is measured from independent cross-sectional samples in each year, allowing for a valid interpretation on how the relative share of employment varies based on the average sectoral intensity of AI adoption, but does not provide strict causal evidence. This methodology ensures a robust and representative analysis within the constraints imposed by the available data and the annual cross-sectional design of the European ICT survey.

Although the panel methodology applied is robust to capture unobserved fixed effects and persistent heterogeneity between groups, it is worth mentioning the possibility of endogeneity derived from reverse causality or the omission of relevant variables. Although it has not been possible to use instrumental variables or experimental methods in this work due to constraints in the available data and in the scope of the project, future research could address this issue using instruments such as delays in technological adoption, specific regulatory shocks on artificial intelligence or historical events that exogenously affect the introduction of AI in certain sectors. Explicitly acknowledging this methodological limitation allows us to prudently interpret our results and opens the door to future lines of research.

4. DESCRIPTIVE ANALYSIS OF AI ADOPTION AND EMPLOYMENT

Before proceeding to the econometric analysis, a descriptive analysis of the main variables used in the sectoral and occupational models is carried out. As mentioned in the previous section, AI adoption by sector is measured from independent cross-sectional samples for European countries.

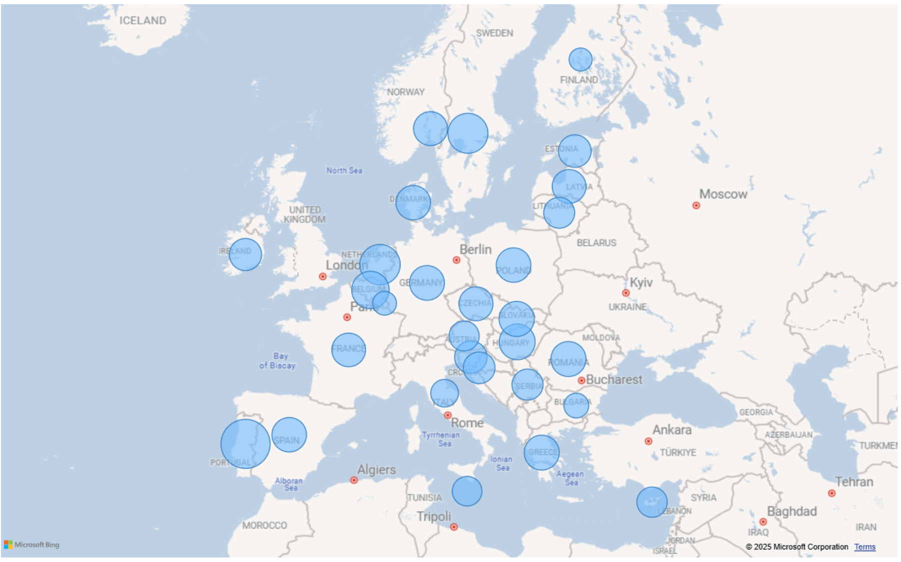


Figure 1. Distribution of IA_Adoption observations by country in Europe (2023-2024)
Source: Authors' elaboration based on Eurostat data (Digital Economy and Society dataset, 2023-2024).

Figure 1 shows the distribution of AI adoption observations for the 29 European countries in the period 2023-2024, indicating a correct homogeneity of the distribution of the data we observe.

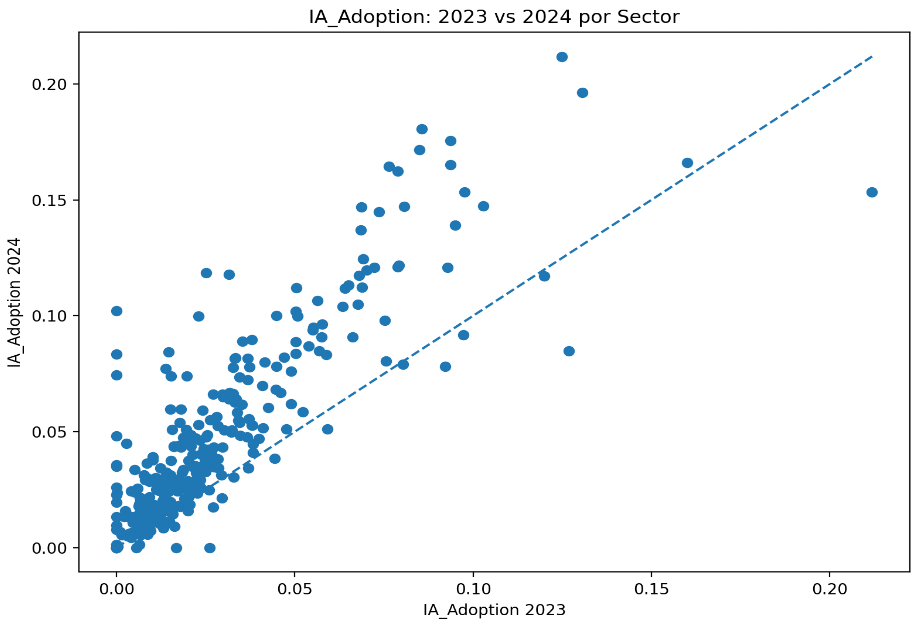
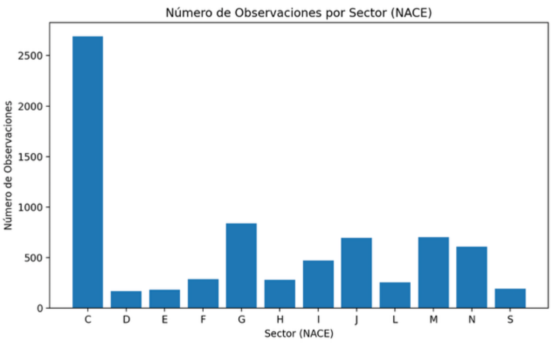


Figure 2. AI adoption comparison by sector: 2023 vs 2024. Source: Authors' elaboration with data from Eurostat (Digital Economy and Society dataset, 2023-2024).

Figure 2 shows a notable growth in the level of AI adoption between 2023 and 2024, with a distribution concentrated in values of less than 5%, indicating a low level of AI implementation in economic sectors in the observed period.



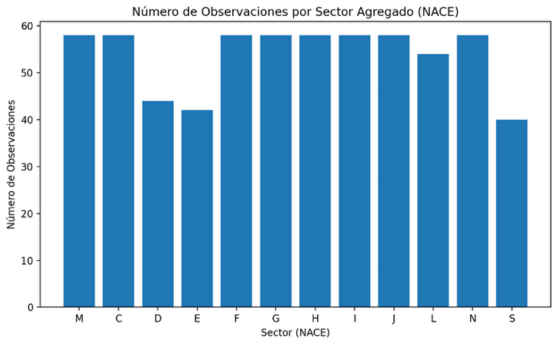


Figure 3 and 4. Number of observations of enterprise-level AI adoption by industry (NACE). Number of AI adoption observations aggregated by sector (sector-country-year, NACE). Source: Authors' elaboration with data from Eurostat (Digital Economy and Society dataset, 2023-2024).

Figure 3 identifies a distribution of observations concentrated in the Manufacturing industry sector (NACE section C) with more than 2500 observations of the level of AI adoption in companies. Figure 4 shows the observations once they are aggregated by sectors, obtaining a more homogeneous distribution for each sector, with 40-60 observations for each sector.

Table 1. Descriptive statistics of the sectoral panel used in the model (2023-2024)

Var. Sector	Media	Desv. Est.	Minimum	Maximum
IA_Adoption	0,0381	0,0378	0,0000	0,2500
Share Sector	0,0569	0,0494	0,0012	0,2528
GDPCap	33140,59	20743,58	8520,00	101450,00
Educ_Rate	0,3991	0,0849	0,2288	0,5811
Unemp_Rate	0,0579	0,0221	0,0260	0,1220
RTI	-0,4221	0,2179	-0,9000	0,4203
NRA	0,2242	0,1412	0,0000	0,5900
NRI	0,1973	0,0776	0,0100	0,3417
RC	0,1939	0,0557	0,0500	0,3956
RM	0,0952	0,0879	0,0000	0,5200
NRM	0,2877	0,1611	0,0200	0,8400
Mean_RTI	-0,4492	0,2122	-0,8911	0,4289

Source: Authors' elaboration based on Eurostat (Digital Economy and Society dataset and EU-LFS, 2023-2024)

Table 1 shows the descriptive statistics of the key variables of the model at the sectoral level: the degree of adoption of AI by companies (`IA_Adoption`), the relative share of sectoral employment (`Share_Sector`), real GDP per capita (`GDPCap`), tertiary education level (`Educ_Rate`), unemployment rate (`Unemp_Rate`), the routine intensity index without weights (`RTI`)) and the routine intensity index with weights (`Mean_RTI`). In addition, the intensity index is disaggregated by sub-tasks (without weights) for each sector: routine cognitive tasks (`CR`), routine manual tasks (`RM`), non-routine analytical tasks (`NRA`), non-routine interactive tasks (`NRI`) and non-routine manual tasks (`NRM`).

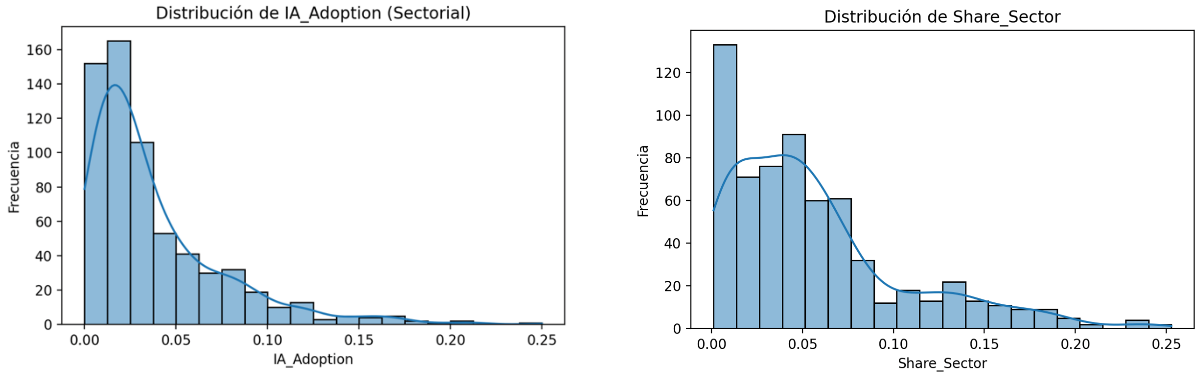


Figure 5 and 6. Distribution of IA_Adoption in the sectoral panel (2023-2024). Distribution of Share_Sector in the sectoral panel (2023-2024). Source: Authors' elaboration based on Eurostat (Digital Economy and Society dataset and EU-LFS).

The main variables of study at the sectoral level are represented by means of frequency histograms. It is observed that the adoption of AI shows relatively low values on average among economic sectors with an average close to 4%, concentrated in values close to zero and some maximum values of 25%, indicating that only a small fraction of sectors reach high levels of adoption and a moderate level of penetration.

The relative share of sectoral employment averages close to 6%, ranging from minimum values of 0.1% to maximum values of 25%, with a more dispersed distribution, which reflects the heterogeneity in the distribution of relative employment between sectors, without a single pattern predominating, although it is more frequent in low values.

The control variables (GDP per capita, educational level and unemployment rate) show significant variability, according to the structural differences between countries and sectors in Europe.

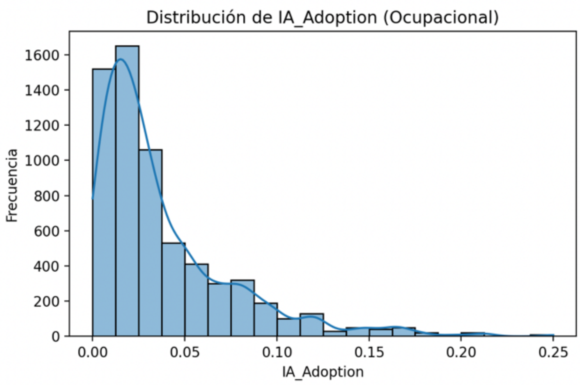
The routine intensity index without weights and the routine intensity index with weights show to be very close, with a negative mean close to -45%, which suggests that, on average, the sectors are not very intensive in routine tasks, with values ranging from the minimum of -89% (very little intensive in routine tasks) to the maximum of 43% (intensive in routine tasks). When analyzing by sub-tasks, an average uniform distribution of values is identified for tasks within NRA, NRI, RC and NRM, with an average close to 20%, while tasks within RM, an average intensity index close to 10% is observed. No alarming maximum or minimum results are observed for the task subcategories.

Table 2. Descriptive statistics of the occupational panel used in the model (2023-2024)

Var. Occupation	Media	Desv. Est.	Minimum	Maximum
IA_Adoption	0,0381	0,0378	0,0000	0,2500
Share_Occupation	0,1000	0,1577	0,0000	1,0000
GDPCap	33140,59	20729,08	8520,00	101450,00
Educ_Rate	0,3991	0,0848	0,2288	0,5811
Unemp_Rate	0,0579	0,0221	0,0260	0,1220
Share Sector	0,0569	0,0494	0,0012	0,2528

Source: Authors' elaboration based on Eurostat (Digital Economy and Society dataset and EU-LFS, 2023-2024)

Table 2 is presented below, which shows the descriptive statistics of the key variables of the model at the occupational level: the degree of adoption of AI by companies (`IA_Adoption`), the relative share of sectoral employment (`Share_Sector`), real GDP per capita (`GDPCap`), tertiary education level (`Educ_Rate`), unemployment rate (`Unemp_Rate`) and the relative share of occupational employment (`Share_Occupation`).



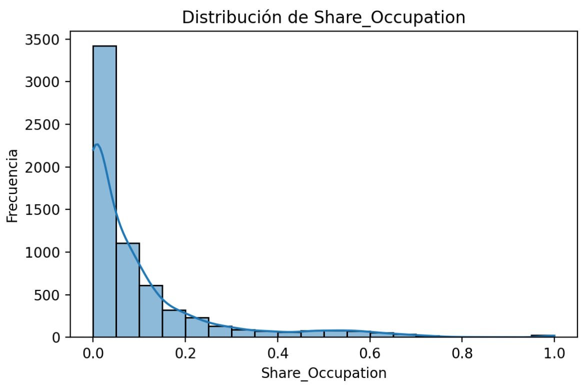


Figure 7 and 8. Distribution of IA_Adoption in the occupational panel (2023-2024). Distribution of Share_Occupation in the occupational panel (2023-2024). Source: Authors' elaboration based on Eurostat (Digital Economy and Society dataset and EU-LFS).

In the same way as the sectoral model, the main variables of study at the occupational level are represented by means of frequency histograms. It is found that the distribution of AI adoption is the same as for the sector, concentrated in low values, which confirms the limited penetration of AI in the European business fabric in the period analysed.

The relative share of occupational employment shows an average somewhat higher than the sectoral average, with an average close to 10%, although with a significantly higher standard deviation and maximum values equal to 100%. The histogram shows a strong concentration in values close to zero, with a progressive decrease in frequencies as the relative weight of certain occupations increases, reflecting the existence of occupational groups that represent a small proportion of employment, compared to others that are much more relevant.

In both panels, no anomalous extreme values are detected that justify the exclusion of variables, although the marked asymmetry in the adoption of AI will be relevant when interpreting the marginal effects in econometric models.

5. ECONOMETRIC RESULTS

The main findings of the econometric models are summarized below, where Table 3 corresponds to the sectoral model[5] (NACE Rev. 2 classification), and Table 4 to the occupational model[6] (ISCO-08 classification). Each table includes the estimated coefficients, standard errors, number of observations and R2 of the estimates of study interest, using MCO.

5.1. Sectoral results

TABLE 3

EFFECTS OF AI ADOPTION ON THE SECTORAL STRUCTURE OF EMPLOYMENT

PANEL DATA WITH FIXED EFFECTS, 2023-2024			
IA_Adoption	0.2576***	(0.0775)	p=0.0009
AI x NACE_C	-0.7550*	(0.4196)	p=0.0725
AI x NACE_D	-0.2682***	(0.0768)	p=0.0005
AI x NACE_E	-0.2484***	(0.0886)	p=0.0052
AI x NACE_F	-0.6467**	(0.2517)	p=0.0104
AI x NACE_G	-0.7006***	(0.2422)	p=0.0040
AI x NACE_H	-0.5521***	(0.1515)	p=0.0003
AI x NACE_I	-0.0900	(0.1518)	p=0.5535
AI x NACE_J	-0.1601**	(0.0658)	p=0.0153
AI x NACE_L	-0.1149*	(0.0697)	p=0.0996
AI x NACE_N	-0.0687	(0.0769)	p=0.3721
AI x NACE_S	-0.1862**	(0.0746)	p=0.0128
R2 (Within)			0.8412
Obs No.			644

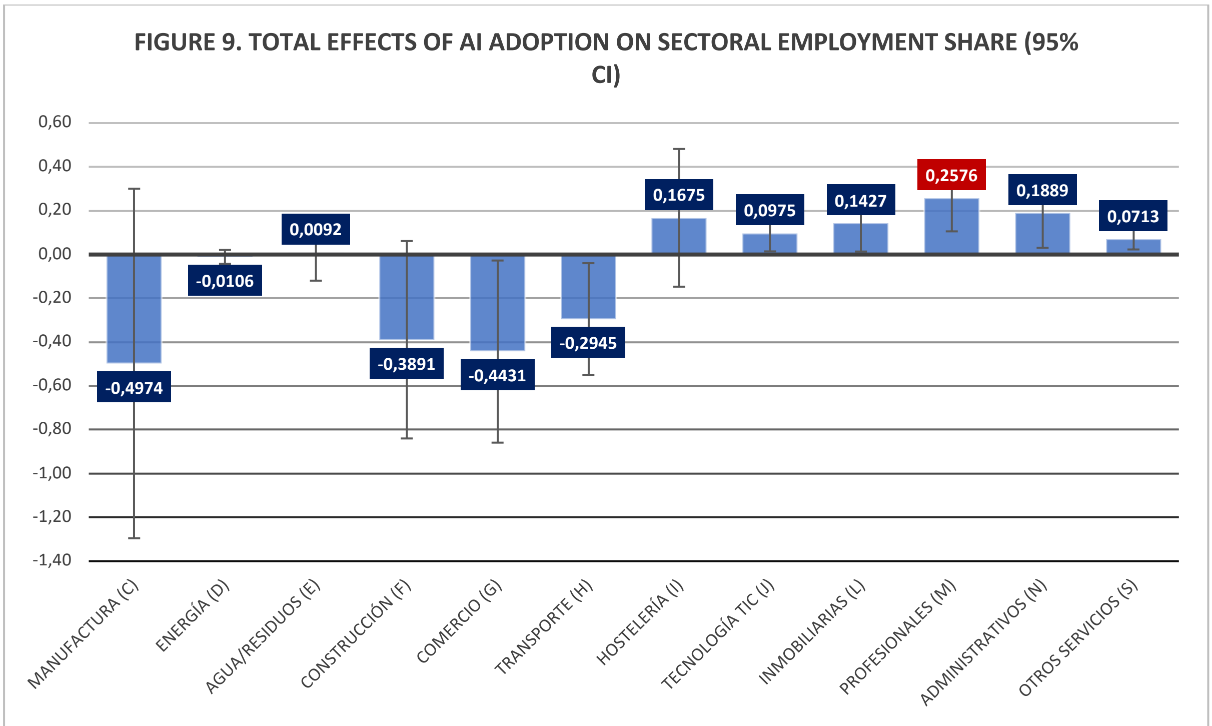
Note: Standard errors in parentheses. (***) 1%, (**) 5%, (*) 10%. Robust clustered bugs.
Control Variables: GDPCap, Educ_Rate, Unemp_Rate
Effects included: Entity, Time

Table 3 reveals that AI adoption is statistically significantly associated with variations in the sectoral structure of employment, where the level of intensity differs depending on the economic sector observed. Together, the explanatory variables of the model manage to

[5] Table A1 (Annex). Full results of the sectoral model: coefficients, robust standard errors and adjustment statistics (Eurostat, 2023-2024)
[6] Table A2 (Annex). Complete results of the occupational model: coefficients, robust standard errors and adjustment statistics (Eurostat, 2023-2024)

explain 84.12% of the variability in the participation of sectoral employment, which is interpreted as a high explanatory power. The interaction coefficients make it possible to identify how the impact of AI differs in each economic sector in relation to the base sector (professional, scientific and technical activities).

The regressor variable `IA_Adoption` refers to the economic sector of professional, scientific and technical activities (corresponding to section M of NACE Rev. 2) established as a base category, with an estimated coefficient that indicates a positive association for the professional services sector. Their interpretation tells us that, for every increase of one percentage point (0.01 in proportional terms) in the aggregate level of AI adoption, relative employment in the professional services sector is associated, on average, with an increase of 0.2576 percentage points, all other factors being equal. This effect is significant with a 99% confidence interval, so it is very unlikely statistically that it is the product of chance.



Note: Total effects calculated as the sum of the coefficient "IA_Adoption" and the interactions with each sector from the panel model with fixed effects by sector-country and time. Vertical bars show 95% confidence intervals. Source: Authors' elaboration based on estimates from PanelOLS with data from Eurostat (Digital Economy and Society dataset and EU-LFS).

Figure 9 shows the total effects of AI adoption in each economic sector[7], calculated as the sum of the base effect and the sectoral differential, allowing a direct interpretation of the impacts in each sector. A heterogeneous association is observed that links AI with increases in the share of employment in certain sectors, and disruptive effects of sectoral displacement in others.

The sector of activities related to information and communications (section J of NACE Rev. 2), the sector of real estate activities (section L of NACE Rev. 2), the sector related to administrative activities and auxiliary services (section N of NACE Rev. 2) and activities

[7] Table A8 (Annex). Total effects of AI adoption on employment share by NACE sector (2023-2024 panel)

classified within other services (section S of NACE Rev. 2) stand out with a positive and significant effect.

In the information and communication (ICT) sector and activities grouped into other services, the effect is moderate and significant where, in terms of estimated effects, it is observed that, for every one percentage point increase in the level of AI adoption, relative employment is associated with an increase of, on average, 0.0975 and 0.0713 percentage points respectively, keeping the other factors constant. These results reflect a positive effect, but statistically lower compared to the professional sector according to the comparison of coefficients represented in Table 1.

In real estate and back-office activities, the effect is strong and significant, where, in estimated terms, relative employment is associated with an increase of 0.1427 and 0.1889 percentage points respectively in these sectors for every one percentage point increase in the level of AI adoption, all other factors being equal. For greater emphasis, it is not possible to observe a statistically different effect (with a 95% confidence interval) to the professional services sector according to the comparison of coefficients in the observed data, therefore, we cannot conclude a different effect in these sectors.

On the other hand, the sector of activities related to wholesale and retail trade, repair of motor vehicles and motorcycles (section G of NACE Rev. 2) and the transport and storage sector (section H of NACE Rev. 2) stand out with a negative and significant effect. Both sectors have a strong and significant negative association that, in estimated terms, the relative share decreases by 0.4431 and 0.2945 percentage points respectively for each increase of one percentage point in the level of AI adoption, keeping the other factors constant.

The rest of the sectors – corresponding to sections C (Manufacturing), D (Supply of electricity, gas, steam and air conditioning), E (Water supply, sanitation activities, waste management and decontamination), F (Construction) and I (Hospitality and food services), according to the NACE Rev. 2 classification – were not significant (with a 95% confidence interval). so there is insufficient evidence that AI adoption has a significantly non-zero effect on the relative employment share in such sectors.

The results at the sectoral level support the idea that in high-skilled sectors that require advanced cognitive skills such as the professional services sector, AI follows a complementary pattern, associated with an increase in the share of employment in the sector, while in low-skilled sectors that do not require advanced cognitive skills, like the commerce sector, AI follows a substitute pattern, associated with a decrease in the share of employment in the sector.

5.2. Occupational outcomes

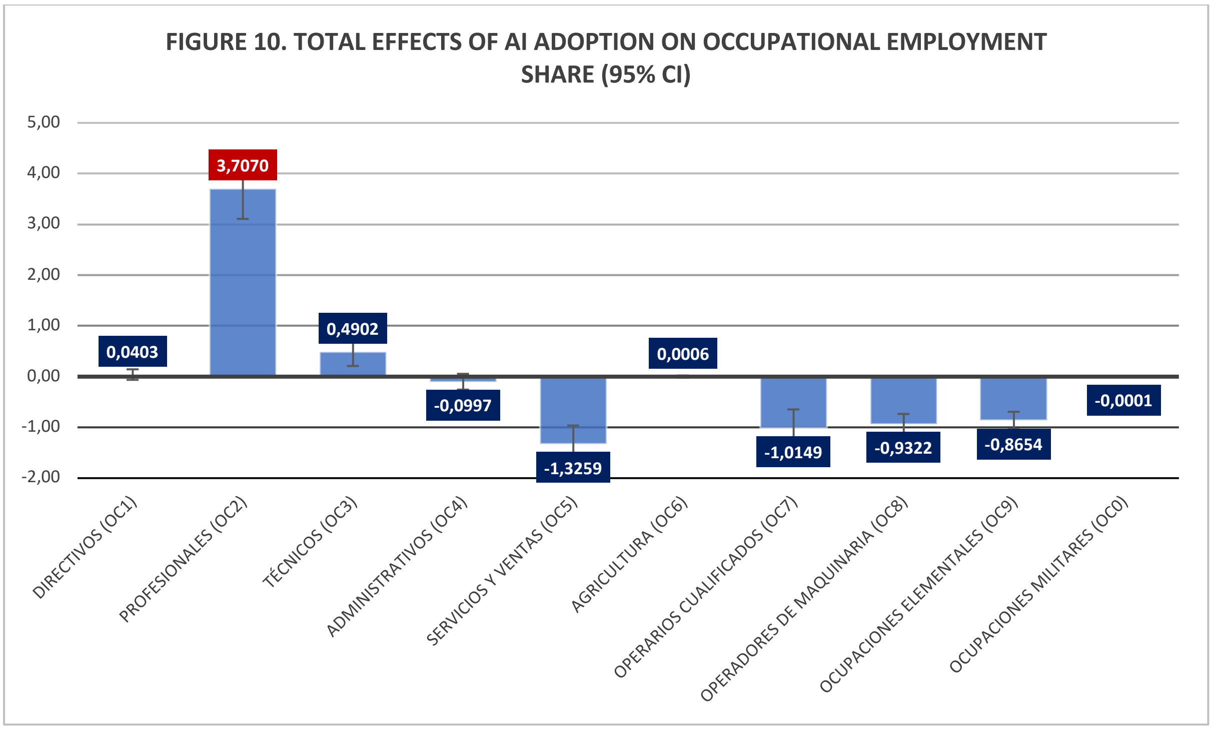
TABLE 4

EFFECTS OF AI ADOPTION ON THE OCCUPATIONAL STRUCTURE OF EMPLOYMENT			
PANEL DATA WITH FIXED EFFECTS, 2023-2024			
IA_Adoption	3.7070***	(0.3058)	p=0.0000
OC1 × IA_Adoption	-3.6667***	(0.2931)	p=0.0000
OC3 × IA_Adoption	-3.2168***	(0.3464)	p=0.0000
OC4 × IA_Adoption	-3.8067***	(0.3552)	p=0.0000
OC5 × IA_Adoption	-5.0329***	(0.4149)	p=0.0000
OC6 × IA_Adoption	-3.7063***	(0.3064)	p=0.0000
OC7 × IA_Adoption	-4.7219***	(0.4540)	p=0.0000
OC8 × IA_Adoption	-4.6392***	(0.3546)	p=0.0000
OC9 × IA_Adoption	-4.5724***	(0.3500)	p=0.0000
OC0 × IA_Adoption	-3.7071***	(0.3058)	p=0.0000
R2 (Within)			0.2661
Obs No.			6440

Note: Standard errors in parentheses. (***) 1%, (**) 5%, (*) 10%. Robust clustered bugs.
Control Variables: GDPCap, Educ_Rate, Unemp_Rate
Effects included: Entity, Time

Table 4 shows that the adoption of AI is significantly associated with variations in the occupational structure of the job and differs according to the hierarchical group observed. Overall, the model manages to explain 26.61% of the variability of the participation of occupational employment in each sector, which indicates that there are other sources of variation not captured by the model's controls. The interaction coefficients allow us to contrast the effect of AI in each occupational group as opposed to the base group (professionals, scientists and intellectuals).

The coefficient of the regressor variable `IA_Adoption` shows a strong positive association of AI adoption in the relative employment of the hierarchical group that includes professionals, scientists and intellectuals (corresponding to the OC2 hierarchical group of ISCO-08), established as the base category. In numerical terms, for every one percentage point increase in the level of AI adoption, the relative employment of professionals increases, on average, by 3.7070 percentage points, if all other factors are held constant. With a p-value < 0.01, it is confirmed that the variance of relative employment for professionals is related to an increase in the adoption of AI, with a 99% confidence interval, therefore, it is statistically unlikely to be the product of chance.



Note: Total effects calculated as the sum of the coefficient "IA_Adoption" and the interactions with each occupational group from the panel model with fixed effects by sector-country and time. Vertical bars show 95% confidence intervals. Source: Authors' elaboration based on estimates from PanelOLS with data from Eurostat (Digital Economy and Society dataset and EU-LFS).

Figure 10 adopts the same methodology as the previous one, which shows the total effects of AI adoption for each hierarchical group[8], calculated as the sum of the base effect and the occupational differential. As in the sectoral analysis, a heterogeneous effect is observed, which associates AI with increases in the employment share of certain groups of occupations and disruptive effects of occupational displacement in others.

With a positive and significant effect, the occupations of technicians and mid-level professionals (group OC3 of the ISCO-08) stand out. In terms of estimated effect, it is observed that, for every increase of one percentage point in the level of AI adoption, relative employment is associated with an increase of, on average, 0.4902 percentage points, all other factors being equal. Therefore, it is a considerable effect but statistically lower and overlapped by the professional sector, observed in the comparison of coefficients in Table 2.

On the other hand, in service and sales occupations (ISCO-08 group OC5), skilled operators (ISCO-08 group OC7), machine operators (ISCO-08 group OC8) and elementary occupations (ISCO-08 group OC9) there is a very significant negative effect, which, in terms of estimated effects, for every increase of one percentage point in the level of AI adoption, Relative employment is associated with a decline of, on average, 1.3259, 1.0149, 0.9322 and 0.8654 percentage points for each sector, respectively, all other factors being equal.

For the rest of the occupations – corresponding to groups OC1 (Directors and managers), OC4 (Administrative support personnel), OC6 (Farmers and skilled agricultural, forestry and fishing

[8] Table A9 (Annex). Total Effects of AI Adoption on Employment Share by Occupation ISCO-08 (Panel 2023-2024)

workers) and OC0 (Military occupations) according to the ISCO-08 classification – the coefficients were not significant, so there is insufficient evidence that the adoption of AI has a non-zero effect on the relative employment share of these occupational groups.

The results at the occupational level support the idea of a heterogeneous effect that differs according to the type of tasks of each hierarchical group. The observations show a complementary effect on the occupations of professionals and technicians, characterized by their high level of qualification and intensive in advanced, creative and non-routine cognitive tasks. On the contrary, a substitutive effect is observed in non-routine occupations characterized by their low level of qualifications and cognitive abilities.

5.3. Conclusions of the econometric results

The econometric results obtained reveal statistically significant associations between the aggregate adoption of artificial intelligence and changes in the sectoral and occupational structure of employment in Europe during the period 2023-2024.

At the sectoral level, a clear pattern of heterogeneity is observed, where sectors that are highly intensive in human capital and advanced cognitive tasks, such as professional, scientific and technical activities (NACE Section M), information and communication (NACE Section J), real estate activities (NACE Section L), and administrative activities and ancillary services (NACE Section N), a higher level of AI adoption is positively related to a higher relative share of employment. This result is in line with the literature that points to a complementarity effect between AI and non-routine cognitive tasks. By contrast, sectors such as commerce (NACE Section G) and transport and warehousing (NACE Section H), which present a less human capital-intensive task profile and more susceptible to routine or semi-routine automation, show strong and significant negative associations with AI adoption. This finding partially supports the hypothesis of sectoral shift of employment towards sectors more intensive in advanced cognitive skills.

In the occupational model, the results reinforce the existence of a heterogeneous pattern according to the nature of the predominant tasks in each occupational group. The adoption of AI is positively associated with a higher relative share of employment in highly skilled occupations, such as scientific and intellectual professionals (ISCO-08 group OC2), and technicians and mid-level professionals (ISCO-08 group OC3), who perform predominantly non-routine cognitive and analytical tasks. On the other hand, lower-skilled occupations or those intensive in non-routine manual tasks, such as service and sales workers (ISCO-08 group OC5), skilled operators (ISCO-08 group OC7), machine operators (ISCO-08 group OC8) and elementary occupations (ISCO-08 group OC9), have significant negative associations with higher levels of AI penetration.

It is important to emphasize that these results reflect statistical associations obtained with sectoral and occupational aggregate data, therefore, individual causal direct effects cannot be conclusively attributed to the adoption of AI.

In short, these results highlight differentiated patterns according to the task profile of sectoral and occupational employment, and provide empirical evidence consistent with recent theories on the heterogeneous impact of advanced technologies on the labor market.

6. MACROECONOMIC MODELS

6.1. Theoretical model of non-routine vs. routine tasks

To understand the possible effects associated with the adoption of artificial intelligence on the structure of sectoral and occupational employment, we propose a simple macroeconomic model based on the theory of routine and non-routine tasks. This model considers that production in a sector can be broken down according to the relative intensity of two types of tasks: those that can be automated (routine tasks) and those that are more difficult to replace (non-routine tasks), typically associated with advanced cognitive or creative skills.

We define:

- lN: proportion of employment with high intensity in non-routine tasks (cognitive, creative).
- lR: proportion of employment with high intensity in routine tasks (mechanical, repetitive).

We assume that sectoral output Y_{it}, in a country i and year t, depends on capital Kit, work on non-routine tasks l_N, and work on routine tasks l_R. We introduce the adoption of AI (`IA_Adoption`) as a potentially complementary factor for non-routine tasks and substitutes for routine tasks, reflected in the following Cobb-Douglas production function:

$$Y_{i,t} = AK^{\alpha}L^{(1-\alpha)}$$

Where:

$$L = [\beta \times (IA\_Adoption \times l_N)^{\rho} + (1-\beta) \times (\frac{l_R}{IA\_Adoption})^{\rho}]^{(1/p)}$$

$$L = l_N + l_R$$

Resulting:

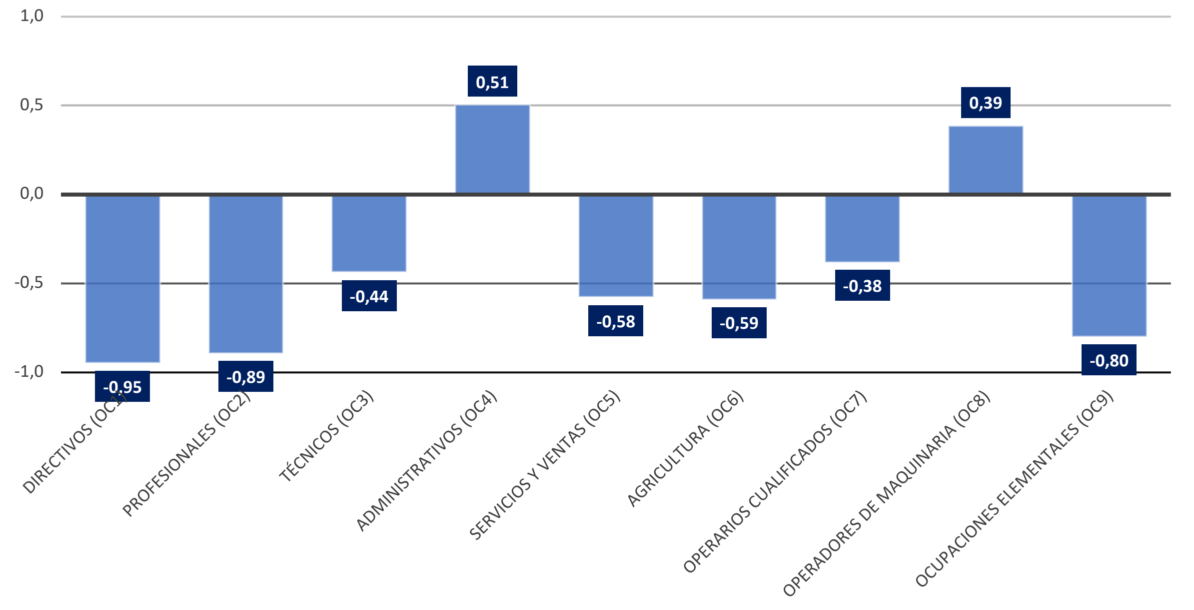
$$Y_{i,t} = AK^{\alpha}[\beta \times (IA\_Adoption \times l_N)^{\rho} + (1-\beta) \times (\frac{l_R}{IA\_Adoption})^{\rho}]^{(1-\alpha)/\rho}$$

- α ∈ (0.1): Elasticity of output with respect to capital.
- ρ ∈ (0,1): ESC substitution parameter between the two work aggregates.
- β ∈ (0.1): Relative weight of non-routine tasks within total work.

Therefore, the model suggests that the association between AI adoption and employment will depend on the composition of work in each sector, as well as on the capital-labor elasticity and the degree of substitution between routine and non-routine tasks. In sectors with a predominance of routine tasks, an increase in AI adoption would tend to be associated with a reduction in relative employment, since increased productivity could replace workers. Conversely, in sectors with a higher proportion of non-routine tasks, AI could complement human labor, raising productivity without necessarily displacing employment.

To analyze how AI adoption relates to employment in different economic sectors, we consider the type of tasks predominant in each occupation. The economic literature has shown that technological change tends to automate repetitive routine tasks, while complementing non-routine tasks that require analytical reasoning, creativity, or interpersonal interaction (Autor, Levy, & Murnane, 2003).

FIGURE 11. ROUTINE TASK INTENSITY INDEX BY OCCUPATIONAL GROUP (Mihaylov & Tijdens, 2019)



Note: Distribution of aggregate RTI at the level of one digit (ISCO-08) using four-digit employment weights by occupation in the Netherlands in 2017 (CBS StatLine). Source: Authors' elaboration based on Mihaylov and Tijdens (2019).

To categorize each occupational group (according to ISCO-08), we used the routine intensity index (RTI) developed by Mihaylov and Tijdens (2019). This index provides a continuous measure that reflects the average degree of routine in each occupation at the European aggregate level, considering the weighted proportion of different types of tasks.

From occupation-specific RTI values, a weighted measure (according to the share of occupational employment, `Share_Occupation`) of the RTI was calculated for each country-year-sector combination. This weighted index (sectoral average RTI) allows for an empirical assessment of whether the relationship between AI adoption and the sectoral structure of employment varies systematically with the intensity of routine tasks.

To empirically test this hypothesis, a panel data model with fixed effects was estimated, with the following econometric specification:

$$Share\_Sector_{i,s,t} = \beta_0 + \beta_1 \times IA\_Adoption_{i,s,t} + \beta_2 \times (IA\_Adoption \times RTI)_{i,s,t} + \gamma_1 \times GDPCap_{i,t} + \gamma_2 \times Educ\_Rate_{i,t} + \gamma_3 \times Unemp\_Rate_{i,t} + +\mu_i + \lambda_t + \mathcal{E}_{i,s,t}$$

Where:

- μi: These are the fixed effects of the entity (sector-country).

- λt: These are the fixed temporal effects (year).
- $\varepsilon_{i,t}$: This is the term error.

In this framework, the coefficient β1 measures the association between AI adoption and sectoral employment when RTI=0 (average level of routine intensity), while β2 captures how this association changes when the relative intensity of routine tasks increases or decreases. Sectors with a higher RTI (more routine tasks) are expected to show a less favorable association with relative employment by increasing AI adoption, while those with a lower RTI (predominance of non-routine tasks) are expected to show a more positive or less negative association.

6.2. Results of the theoretical model of non-routine vs. routine tasks

Table 5 presents the econometric results of the first theoretical model, which analyzes whether routine task intensity regulates the association between AI adoption and sectoral participation in employment[9].

TABLE 5

EFFECT OF AI ADOPTION ON THE SECTORAL STRUCTURE OF EMPLOYMENT BY THE ROUTINE TASK INTENSITY INDEX (RTI)

PANEL DATA WITH FIXED EFFECTS, 2023-2024			
IA_Adoption	0.0971	(0.2785)	p=0.7276
IA_Adoption x Mean_RTI	0.1467	(0.3867)	p=0.7046
R2 (Within)			0.0239
Obs No.			644

Note: Standard errors in parentheses. (***) 1%, (**) 5%, (*) 10%. Robust clustered bugs.
Control Variables: GDPCap, Educ_Rate, Unemp_Rate
Effects included: Entity, Time

The coefficient of `AI × RTI` interaction shows the effect of AI adoption on sectoral relative employment when the intensity of routine tasks varies, with a positive result of 0.1467 percentage points, but it is not statistically significant. Similarly, the coefficient of the main variable `IA_Adoption` relates the effect of an increase in the level of AI adoption when the intensity in routine tasks is equal to zero, with a positive result of 0.0971 percentage points, but again, not significant. These results indicate that, with the data available for the period 2023-2024, it cannot be concluded that routine employment intensity explains the previously observed heterogeneity in the effects of AI adoption on sectoral relative employment. In addition, the low explanatory capacity of the model (R^2 within = 0.0239) suggests that there are factors not considered in the model that could explain the variability of the sectoral structure of employment.

[9] Table A3 (Annex). Full model results with RTI: coefficients, robust standard errors and fit statistics (Eurostat, 2023-2024)

In conclusion, the first theoretical model does not allow to confirm the initial hypothesis according to which routine work intensity significantly regulates the relationship between AI adoption and the sectoral structure of employment. Therefore, in the next section we will proceed to explore whether a more detailed decomposition into the task-specific subcomponents can provide additional evidence that clarifies the observed patterns.

6.3. Theoretical model of sub-tasks

To obtain the routine intensity index, Mihaylov and Tijdens (2019) propose the following model:

$$RTIk = RCk + RMk - NRAk - NRIk - NRMk$$

Where RTI indicates the intensity in routine tasks of occupation k, composed of five categories of tasks: routine cognitive (CR), routine manuals (RM), non-routine analytical (NRA), non-routine interactive (NRI) and non-routine manuals (NRM).

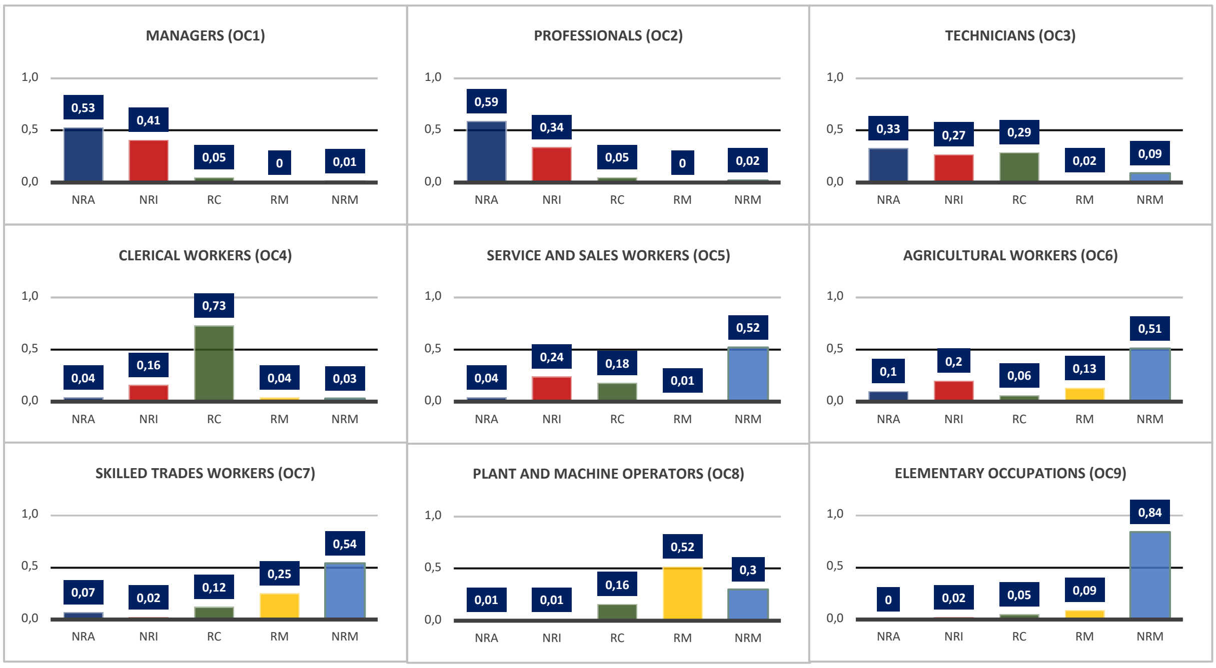


Figure 12. Sub-task intensity index by occupational group (Mihaylov & Tijdens, 2019) – unweighted calculation. Average proportions of the five task categories (cognitive routine – CR, routine manuals – RM, non-routine analytical – NRA, non-routine interactive – NRI, and non-routine manuals – NRM) for each of the nine ISCO-08 single-digit occupations, calculated as a simple arithmetic mean of the 427 four-digit occupations (without applying employment weights). Source: Authors' elaboration based on Mihaylov and Tijdens (2019).

To explore in detail how each specific category of tasks influences the relationship between AI adoption and the sectoral structure of employment, weighted average proportions were constructed for each of these five categories (NRA, NRI, RC, RM, NRM) by sector-country-year. Because Mihaylov and Tijdens (2019) do not directly provide the values of these categories at the level of single-digit occupational groups (OC1-OC9), we calculate these averages manually. To do this, the tables with the 427 detailed occupations (four digits) of the original study are used and a simple arithmetic mean is made for each occupational category added, without weighting by employment, because we did not have the specific weights of employment used by the authors for the RTI. Since the proportions add up to approximately

1, there is a strong multicollinearity, which is why routine cognitive tasks (CR) are omitted and established as the base category, which represents the traditional pattern of tasks most susceptible to classical automation and serves as a reference point.

To empirically test this theoretical model, we estimate a panel data model with fixed effects by entity (sector-country) and temporal (year), using the following econometric specification:

$$Share\_Sector_{i,s,t} = \beta_0 + \beta_1 \times IA_{i,s,t} + \beta_2 \times IA_{i,s,t} \times NRA_{i,s,t} + \beta_3 \times IA_{i,s,t} \times NRI_{i,s,t} + \beta_4 \times IA_{i,s,t} \times RM_{i,s,t} + \beta_5 \times IA_{i,s,t} \times NRM_{i,s,t} + \gamma_1 \times NRA_{i,s,t} + \gamma_2 \times NRI_{i,s,t} + \gamma_3 \times RM_{i,s,t} + \gamma_4 \times NRM_{i,s,t} + \delta_1 \times GDPCap_{i,t} + \delta_2 \times Educ\_Rate_{i,t} + \delta_3 \times Unemp\_Rate_{i,t} + +\mu_i + \lambda_t + \mathcal{E}_{i,s,t}$$

Where:

- IA: IA_Adoption
- µi: These are the fixed bills of exchange by entity (sector-country).
- λt: These are the fixed temporal effects (year).
- $\varepsilon_{i,t}$: This is the term error.

In this specification, the coefficient β_1 measures the effect of AI adoption on sectoral employment share when the proportion of routine cognitive tasks (CR) is equal to 1. The coefficients β_2, β_3, β_4 and β_5 capture how this effect varies when the proportion of non-routine, non-routine interactive, routine manual and non-routine manual analytical tasks, respectively, increases, always compared to the routine cognitive tasks omitted as a base category. This strategy allows us to assess in detail whether AI adoption is differentially associated with sectoral employment share according to the specific type of tasks predominant in each sector.

6.4. Results of the theoretical model of sub-tasks

Table 6 shows the results of the theoretical model that considers the detailed decomposition of tasks into five specific categories[10] (non-routine analytical, non-routine interactive, routine cognitive, routine manuals, and non-routine manuals).

[10] Table A4 (Annex). Complete results of the model by sub-tasks: coefficients, robust standard errors and fit statistics (Eurostat, 2023-2024)

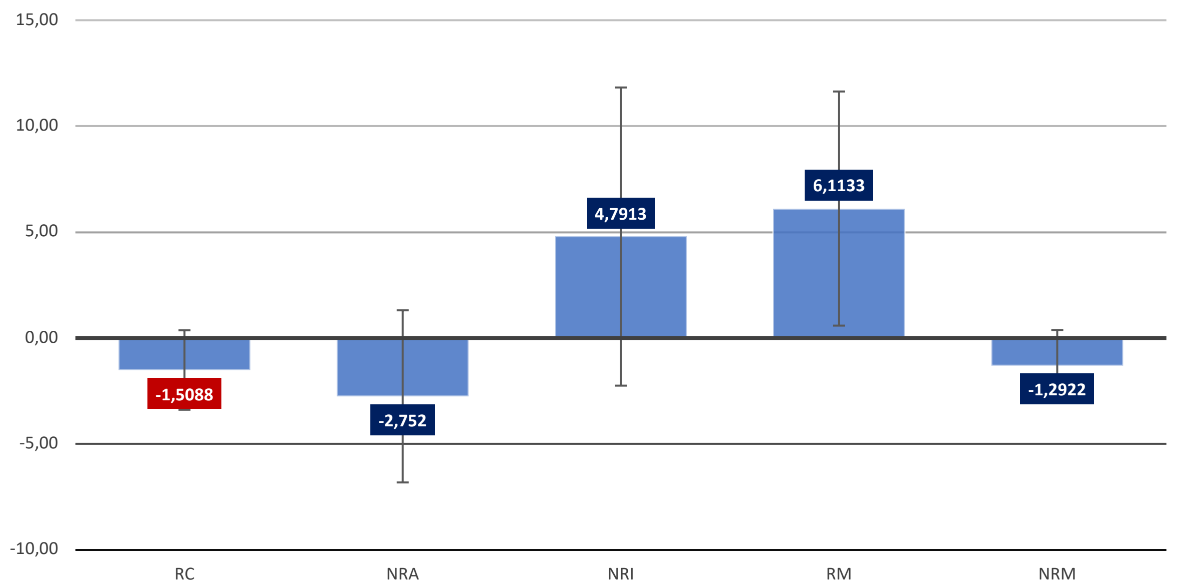
TABLE 6

EFFECT OF AI ADOPTION ON THE SECTORAL STRUCTURE OF EMPLOYMENT BY SUB-TASKS			
PANEL DATA WITH FIXED EFFECTS, 2023-2024			
IA_Adoption	-0.5088	(0.9563)	p=0.1152
AI x NRA	-1.2431	(1.4655)	p=0.3966
IA x NRI	6.3001	(4.4038)	p=0.1531
AI x RM	7.6221**	(3.7066)	p=0.0402
IA x NRM	0.2166	(0.6198)	p=0.7269
R2 (Within)			0.2008
Obs No.			644

Note: Standard errors in parentheses. (***) 1%, (**) 5%, (*) 10%. Robust clustered bugs.
Control Variables: GDPCap, Educ_Rate, Unemp_Rate
Effects included: Entity, Time

The base category chosen for this model is that of routine cognitive tasks (CR), which represents the classic pattern susceptible to automation. In contrast, the model explains 20.08% of the variability of the sectoral participation of employment, which indicates that there are explanatory variables not included in the model.

FIGURE 13. TOTAL EFFECTS OF AI ADOPTION ACCORDING TO THE SUB-TASK INTENSITY INDEX (MIHAYLOV & TIJDENS, 2019) (95% CI)



Note: Total effects calculated as the sum of the coefficient "IA_Adoption" and the interactions with each sub-task (RC, NRA, NRI, RM, NRM) from the panel model with fixed effects by sector-country and time. Vertical bars show 95% confidence intervals. Source: Authors' elaboration based on regression results.

The total effect of AI adoption on the sectoral share of employment by sub-tasks[11] is statistically significant only in sectors dominated by routine manual tasks (RM), with a positive coefficient of 6.1133 percentage points. This implies that, in sectors with a predominance of repetitive manual activities, the adoption of AI is associated with a higher relative share of employment.

For the rest of the subtasks, the total effects were not statistically significant, therefore, these results indicate limited evidence on the explanatory capacity of the individual subtasks in the observed sectoral heterogeneity. The effects obtained should be interpreted with caution due to the limited time length of the available data and the use of unweighted simple averages for task indicators.

6.5. Conclusions of the theoretical models (RTI and sub-tasks)

The results obtained in both theoretical models indicate that, with the currently available data, the theory based on routine work intensity does not provide a solid and generalized explanation for the heterogeneity observed in the effects of AI adoption on sectoral employment.

In the first theoretical model, we found no statistical evidence indicating that routine employment intensity significantly conditions the relationship between AI and sectoral employment. On the other hand, when carrying out a more detailed analysis by breaking down tasks into specific subcategories, the only clear and statistically significant association was that of routine manual tasks, showing a positive relationship with the relative share of sectoral employment. This result could suggest that certain sectors with a predominance of manual repetitive tasks could benefit relatively more from AI adoption, although this finding should be interpreted with caution. The widespread lack of significance in the other sub-tasks suggests that AI adoption could be generating patterns of transformation in the structure of employment that are not fully captured with the classic analytical frameworks of routine and non-routine tasks.

These findings highlight the need for future research with more extensive databases over time and more detailed at the microeconomic level. Only in this way will it be possible to clearly identify the specific mechanisms through which artificial intelligence impacts the sectoral and occupational structure of employment.

[11] Table A10 (Annex). Total Effects: AI Adoption and Sectoral Employment Share by Task Category (NRA, NRI, RC, NRM), 2023-2024

7. ROBUSTNESS TESTS

To ensure the robustness of the results obtained in the sectoral and occupational models, additional tests were carried out to evaluate two fundamental assumptions of the econometric estimates: the absence of severe multicollinearity and the homoscedasticity of the residuals.

First, the Variance Inflation Factor (FIV) was calculated to detect possible multicollinearity problems. The results showed that, in the sectoral model[12], most of the variables presented FIV below the critical threshold of 10. However, the IA_Adoption variable and its interaction with the information and communications activities sector (section J of NACE) exhibited slightly higher values of 14.7 and 16.2, respectively. In the occupational model[13], `IA_Adoption` presented a FIV of 10.1, placing it at the recommended limit, while the rest of the variables and interactions showed acceptable values below 5. These higher values can be explained by the simultaneous inclusion of multiple interactions with sectoral and occupational dummies, causing multicollinearity between the variables.

Second, the Breusch-Pagan test was applied[14] to assess the presence of heteroskedasticity, with the following hypotheses:

- Null hypothesis (H_0): the residuals are homoscedastic (constant variance).
- Alternative hypothesis (H1): the residuals are heteroskedastic.

The results clearly revealed the presence of heteroskedasticity in both sectoral and occupational models ($p < 0.001$), therefore, to correct this problem, robust standard errors clustered at the entity level (sector-country) were used in all estimates. This correction ensures that the statistical inferences are valid against the non-constant variance and possible intra-group correlations detected.

In summary, robustness tests indicate that, although there is some moderate collinearity due to the specification of the models with multiple interactions, this is not severe enough to substantially affect the results, therefore, they are not omitted from the models as they are relevant to the study. Likewise, the procedures adopted to correct heteroskedasticity ensure the robustness and consistency of the conclusions presented in this thesis.

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[12] Table A11 (Annex). Variance Inflation Factors (VIF) of the sectoral model, panel 2023-2024
[13] Table A12 (Annex). Variance Inflation Factors (VIF) of the occupational model, panel 2023-2024
[14] Table A13 (Annex). Breuch-Pagan heteroskedasticity test by panel type (sector and occupational)

8. DISCUSSION OF RESULTS AND IMPLICATIONS

8.1. Contrast with theory

The results obtained in this research indicate heterogeneous associations between AI adoption and the relative share of sectoral and occupational employment in Europe during the period 2023-2024. These findings were contrasted with the classical theoretical framework based on the theory of routine and non-routine tasks, according to which automation should especially replace those routine tasks and complement non-routine tasks.

However, our results did not fully support this theory. The model based on the routine intensity index (RTI) aggregated by sector did not show clear significant effects, indicating that the classical theory fails to explain the patterns observed in new artificial intelligence technologies on the sectoral structure of employment. Disaggregation into specific subcategories of tasks (sub-tasks) offered a single significant result in routine manual (RM) tasks, suggesting that AI could specifically complement repetitive manual processes. This result disaggregated by sub-tasks differs from classical theories, and contradicts the hypothesis that automation replaces repetitive tasks, easily replaced by machinery or advanced technologies.

In short, our results suggest that the recent adoption of AI could be generating transformations in the European labour market through mechanisms not yet fully explained by existing theories. However, we emphasize the limitations of the period and the absence of microeconomic data on employment. However, this opens the door to future research focused on identifying patterns that explain, empirically, how new technologies, especially generative AI, impact heterogeneously on sectors and occupations in the European labour framework.

8.2. Sectoral and policy implications

Although the results do not allow definitive causal relationships to be established, the observed patterns offer relevant implications for both policymakers and companies. At the industry level, human capital-intensive sectors (such as professional and technology services) show positive associations with AI adoption, suggesting that these sectors are better positioned to benefit from intelligent automation. On the other hand, low-skilled sectors such as trade or transport have negative correlations, which could lead to relative job losses if adequate transition measures are not implemented.

At the occupational level, there is a trend towards the displacement of employment towards occupations with high cognitive content (professional, technical), to the detriment of manual occupations or repetitive services. This dynamic can aggravate labor inequalities if it is not anticipated with specific policies.

In this context, it is essential to design active employment policies focused on:

- **Continuous training and retraining**, with special emphasis on digital skills, data analysis and AI literacy for workers in vulnerable sectors.

- **Incentives for sectoral reconversion**, which support the transition of SMEs towards business models that integrate technology without destroying jobs.
- **Job protection and guidance systems**, such as temporary transition allowances or personalised public guidance services, especially in regions more exposed to technological change.

This vision is aligned with the approaches of Acemoglu and Johnson (2023), who warn that technological development does not automatically guarantee improvements in general well-being. According to the authors, the direction of technological change can be biased towards "excessive" automation if it is not explicitly aimed at complementing and empowering the worker. Therefore, the role of the State should not be limited to cushioning the negative effects of technological change, but also to actively model the incentives and direction of innovation, promoting those applications of AI that enhance human capabilities and generate shared value.

The European experience with previous digitalisation shows that the effects are not homogeneous or immediate, therefore, designing proactive policies adapted to each productive context will be key for artificial intelligence to contribute to inclusive and sustainable growth.

9. CONCLUSIONS AND LIMITATIONS

9.1. Synthesis of main findings

This work investigated how the adoption of artificial intelligence by companies relates to the sectoral and occupational structure of employment in Europe during the period 2023-2024, using aggregated data and panel econometric models. The results obtained reveal heterogeneous associations of AI across different branches of activity and occupational categories. At the sectoral level, AI adoption was associated with relative increases in employment in knowledge-intensive sectors (e.g. professional and technology services) and, in contrast, with declines in traditionally less skilled or more routine sectors, such as trade and transport. At the occupational level, a shift in the composition of employment was also observed, where high-skilled occupations, intensive in advanced cognitive tasks (such as scientific-intellectual and technical professionals), increased their relative participation, while lower-skilled occupations (such as service and sales jobs) tended to reduce their relative weight under higher levels of AI adoption.

In relation to the main hypothesis that AI adoption heterogeneously affects employment according to the nature of the tasks, the resulting evidence is mixed. When contrasting these findings with the theoretical framework of routine vs. non-routine tasks, mixed evidence was found. On the one hand, the aggregate patterns are consistent with the idea that AI is benefiting more non-routine/skilled sectors and jobs, partially aligning with the hypothesis raised. However, formal econometric tests based on the global routine intensity index (RTI) did not show a clear differential effect. The interaction coefficient between AI and the average routine intensity level of each sector was not statistically significant. This indicates that, considering all sectors together, the general routine degree of tasks does not significantly explain the heterogeneity observed. However, when the analysis was broken down by task subcategories, a remarkable specific result emerged. In sectors dominated by routine manual tasks, AI adoption was associated with a significant increase in employment share. In other words, only in that particular category of tasks (manual-routine) did AI show a clear positive relationship with employment, perhaps suggesting an unexpected complementarity effect (e.g., AI could be supporting certain repetitive manual tasks rather than completely replacing workers). In the other categories of analytical or cognitive tasks, no statistically significant effects were found. In summary, the hypothesis is partially confirmed, where sectoral and occupational heterogeneity is robust, but RTI indices and fine task decomposition explain this heterogeneity only to a limited extent. This suggests that other factors (e.g., work organization or company-specific technology strategy) also mediate the impact of AI, an aspect that future research should explore with more disaggregated data and longer time series.

Taken together, these findings indicate that the recent adoption of AI in Europe has not had a uniform impact. Relative winners and losers were observed, where human capital-intensive sectors and high-skilled occupations appear, in this initial phase, as the relative winners, while low-skilled sectors (and their corresponding routine jobs) have seen their share of employment decrease. At the same time, the classic distinction between routine and non-routine tasks turned out to be too aggregated to fully explain the variations, with only one subcategory, routine manual tasks, turning out to be statistically significant. These conclusions provide specific empirical evidence on the European labour market in 2023-2024, where there is no effect of massive job destruction by AI in net terms, but a structural readjustment where employment is being redistributed towards activities and occupations more oriented towards advanced knowledge, to the detriment of those that are more routine and less specialised.

9.2. Limitations of the study

The conclusions of this study should be considered in the light of several important limitations, both methodological and data:

Firstly, the time horizon analysed is very limited. Spanning only two years (2023 and 2024), the study captures only the short-term impact of AI adoption. This reduces the ability to identify long-term trends or dynamic effects. Such a short period also increases the sensitivity of the results to transitory or conjunctural events typical of those years.

Second, the analysis was based on aggregated data by sector and occupation, which makes it impossible to establish direct causal relationships at the microeconomic level. Working with sector-country averages, we cannot say that AI "causes" certain changes in individual jobs, as unobserved factors correlated with both AI adoption and employment (e.g., regulatory changes or demand shocks in certain sectors) could play a role. While the use of country and year fixed effects partly controls for some heterogeneities, the risk of bias for omitted variables remains. In summary, our results show significant associations between AI and employment, but do not demonstrate strict causality.

Third, there are limitations to the AI adoption data used. The main source (Eurostat ICT survey of companies) offers a broad indicator on the use of "some AI technology", but does not distinguish between types of AI (e.g. generative AI vs. other applications) nor does it provide detailed information on the intensity or quality with which AI is used in production processes. Therefore, the lack of a specific indicator of generative AI is particularly relevant, given the emphasis of the current discussion on this type of technology.

Fourthly, the measures used to characterise the content of tasks in each sector/occupation entail simplifications. The aggregate routine intensity index (RTI) assigned to each sector comes from averages based on previous data (and in another context, the Netherlands, 2017), so this index may not perfectly reflect differences between countries or capture cross-sectoral nuances. In the disaggregation by sub-tasks, it was necessary to assume equal weightings, which introduces a possible bias, since not all tasks have the same quantitative relevance in each sector, and by not weighting by employment, the measure of sub-tasks could over-represent or under-represent certain activities.

Finally, sample size and specification could influence the robustness of some results. With only 644 observations on the sectoral panel and multiple interaction variables, statistical power is limited to detect more subtle effects. Some estimated coefficients (especially in the occupational model) are marginally significant, so they should be interpreted with caution. If more years or data at a lower level of employment aggregation were available, the estimates could be more accurate.

9.3. Future research agenda

Given the limitations and findings of this study, several future lines of research are identified that could expand and strengthen knowledge about AI and employment:

- **Analysis with individual and business microdata**: Incorporating data at the company or worker level would allow for a clearer identification of the causal mechanisms by which AI affects employment (for example, knowing if certain tasks within jobs are automated, or if AI creates new complementary roles).
- **Extension of the time horizon**: It is essential to extend the study period beyond 2024. An analysis covering developments over the medium to long term (e.g., the next 5 to 10 years) would capture dynamic effects of AI adoption, allowing us to observe whether the trends of 2023-2024 are consolidated, reversed, or new dynamics emerge (such as possible employment recoveries after initial adjustments).
- **Improvements in task and technology measurement**: Developing task indices adjusted for employment weight at the national or sectoral level could provide a more accurate representation of the actual labor structure. For example, if sub-tasks are weighted by the number of workers who actually perform them in each sector, routine vs. non-routine analyses would be more accurate.
- **Analysis with specific indicators of generative AI**: Future surveys could separate the adoption of generative AI from other applications, which would allow us to investigate whether certain classes of AI have different effects on employment.

In conclusion, expanding research in these directions will contribute to a better understanding of how AI is shaping the labour market, offering a stronger basis for formulating appropriate policies. The rapid evolution of AI makes it imperative to continuously update the analysis with new data and methods, so that academics and public officials can anticipate and manage its socio-economic impacts as effectively and equitably as possible.

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ANNEX

Table A1. Full results of the sector model (panel data).

PanelOLS Estimation Summary

Dep. Variable:	Share_Sector	R-squared:	0.8412
Estimator:	PanelOLS	R-squared (Between):	0.3228
No. Observations:	644	R-squared (Within):	0.8412
Date:	Tue, May 20 2025	R-squared (Overall):	0.8347
Time:	21:34:09	Log-likelihood	1620.7
Cov. Estimator:	Clustered		
		F-statistic:	119.79
Entities:	29	P-value	0.0000
Avg Obs:	22.207	Distribution:	F(26,588)
Min Obs:	16.000		
Max Obs:	24.000	F-statistic (robust):	2.338e+05
		P-value	0.0000
Time periods:	2	Distribution:	F(26,588)
Avg Obs:	322.00		
Min Obs:	318.00		
Max Obs:	326.00		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
IA_Adoption	0.2576	0.0775	3.3248	0.0009	0.1054	0.4097
GDPCap	3.693e-08	3.439e-07	0.1074	0.9145	-6.386e-07	7.124e-07
Educ_Rate	-0.0522	0.0276	-1.8897	0.0593	-0.1064	0.0021
Unemp_Rate	-0.0027	0.0542	-0.0502	0.9600	-0.1091	0.1037
C(NACE)[M]	0.0635	0.0170	3.7373	0.0002	0.0301	0.0968
C(NACE)[C]	0.1863	0.0251	7.4141	0.0000	0.1369	0.2356
C(NACE)[D]	0.0269	0.0155	1.7354	0.0832	-0.0035	0.0572
C(NACE)[E]	0.0271	0.0156	1.7420	0.0820	-0.0035	0.0577
C(NACE)[F]	0.0969	0.0160	6.0696	0.0000	0.0656	0.1283
C(NACE)[G]	0.1682	0.0168	10.009	0.0000	0.1352	0.2012
C(NACE)[H]	0.0814	0.0155	5.2481	0.0000	0.0510	0.1119
C(NACE)[I]	0.0637	0.0161	3.9619	0.0001	0.0321	0.0953
C(NACE)[J]	0.0529	0.0159	3.3166	0.0010	0.0216	0.0842
C(NACE)[L]	0.0235	0.0157	1.4926	0.1361	-0.0074	0.0544
C(NACE)[N]	0.0497	0.0165	3.0126	0.0027	0.0173	0.0821
C(NACE)[S]	0.0378	0.0156	2.4233	0.0157	0.0072	0.0685
C(NACE)[T.C]:IA_Adoption	-0.7550	0.4196	-1.7995	0.0725	-1.5790	0.0690
C(NACE)[T.D]:IA_Adoption	-0.2682	0.0768	-3.4924	0.0005	-0.4190	-0.1174
C(NACE)[T.E]:IA_Adoption	-0.2484	0.0886	-2.8026	0.0052	-0.4225	-0.0743
C(NACE)[T.F]:IA_Adoption	-0.6467	0.2517	-2.5691	0.0104	-1.1411	-0.1523
C(NACE)[T.G]:IA_Adoption	-0.7006	0.2422	-2.8927	0.0040	-1.1763	-0.2249
C(NACE)[T.H]:IA_Adoption	-0.5521	0.1515	-3.6443	0.0003	-0.8497	-0.2546
C(NACE)[T.I]:IA_Adoption	-0.0900	0.1518	-0.5929	0.5535	-0.3882	0.2082
C(NACE)[T.J]:IA_Adoption	-0.1601	0.0658	-2.4326	0.0153	-0.2893	-0.0308
C(NACE)[T.L]:IA_Adoption	-0.1149	0.0697	-1.6493	0.0996	-0.2517	0.0219
C(NACE)[T.N]:IA_Adoption	-0.0687	0.0769	-0.8931	0.3721	-0.2197	0.0824
C(NACE)[T.S]:IA_Adoption	-0.1862	0.0746	-2.4972	0.0128	-0.3327	-0.0398

F-test for Poolability: 0.5168
P-value: 0.9839
Distribution: F(29,588)

Included effects: Entity, Time

Table A2. Full results of the occupational model (panel data).

PanelOLS Estimation Summary

Dep. Variable:	Share_Occupation	R-squared:	0.2661
Estimator:	PanelOLS	R-squared (Between):	-5.179e+06
No. Observations:	6440	R-squared (Within):	0.2661
Date:	Tue, May 20 2025	R-squared (Overall):	0.2661
Time:	23:57:13	Log-likelihood	3753.6
Cov. Estimator:	Clustered		
		F-statistic:	70.064
Entities:	29	P-value	0.0000
Avg Obs:	222.07	Distribution:	F(33,6377)
Min Obs:	160.00		
Max Obs:	240.00	F-statistic (robust):	-2.326e+18
		P-value	1.0000
Time periods:	2	Distribution:	F(33,6377)
Avg Obs:	3220.0		
Min Obs:	3180.0		
Max Obs:	3260.0		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
IA_Adoption	3.7070	0.3058	12.123	0.0000	3.1076	4.3064
GDPCap	2.758e-18	2.095e-16	0.0132	0.9895	-4.079e-16	4.134e-16
Educ_Rate	5.735e-14	8.543e-12	0.0067	0.9946	-1.669e-11	1.68e-11
Unemp_Rate	4.089e-14	4.486e-12	0.0091	0.9927	-8.752e-12	8.834e-12
C(NACE)[C]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[D]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[E]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[F]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[G]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[H]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[I]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[J]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[L]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[M]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[N]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(NACE)[S]	0.0486	0.0105	4.6335	0.0000	0.0280	0.0691
C(ISCO_08)[T.OC0]	-0.0485	0.0105	-4.6277	0.0000	-0.0691	-0.0280
C(ISCO_08)[T.OC1]	0.0108	0.0105	1.0317	0.3023	-0.0098	0.0314
C(ISCO_08)[T.OC3]	0.1151	0.0149	7.7053	0.0000	0.0858	0.1444
C(ISCO_08)[T.OC4]	0.0453	0.0124	3.6598	0.0003	0.0210	0.0696
C(ISCO_08)[T.OC5]	0.1604	0.0185	8.6784	0.0000	0.1242	0.1967
C(ISCO_08)[T.OC6]	-0.0454	0.0105	-4.3207	0.0000	-0.0659	-0.0248
C(ISCO_08)[T.OC7]	0.1115	0.0174	6.4114	0.0000	0.0774	0.1456
C(ISCO_08)[T.OC8]	0.0759	0.0146	5.1968	0.0000	0.0473	0.1045
C(ISCO_08)[T.OC9]	0.0891	0.0140	6.3768	0.0000	0.0617	0.1165
C(ISCO_08)[T.OC0]:IA_Adoption	-3.7071	0.3058	-12.123	0.0000	-4.3065	-3.1076
C(ISCO_08)[T.OC1]:IA_Adoption	-3.6667	0.2931	-12.511	0.0000	-4.2412	-3.0921
C(ISCO_08)[T.OC3]:IA_Adoption	-3.2168	0.3464	-9.2863	0.0000	-3.8959	-2.5377
C(ISCO_08)[T.OC4]:IA_Adoption	-3.8067	0.3552	-10.717	0.0000	-4.5029	-3.1104
C(ISCO_08)[T.OC5]:IA_Adoption	-5.0329	0.4149	-12.129	0.0000	-5.8462	-4.2195
C(ISCO_08)[T.OC6]:IA_Adoption	-3.7063	0.3064	-12.098	0.0000	-4.3069	-3.1058
C(ISCO_08)[T.OC7]:IA_Adoption	-4.7219	0.4540	-10.402	0.0000	-5.6118	-3.8320
C(ISCO_08)[T.OC8]:IA_Adoption	-4.6392	0.3546	-13.083	0.0000	-5.3343	-3.9441
C(ISCO_08)[T.OC9]:IA_Adoption	-4.5724	0.3500	-13.066	0.0000	-5.2584	-3.8864

F-test for Poolability: 5.318e-14
P-value: 1.0000
Distribution: F(29,6377)

Included effects: Entity, Time

Table A3. Complete model results with RTI (panel data).

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:          Share_Sector   R-squared:                        0.0240
Estimator:                  PanelOLS   R-squared (Between):             -0.3278
No. Observations:                644   R-squared (Within):               0.0239
Date:               Thu, May 22 2025   R-squared (Overall):             -0.1808
Time:                       19:48:10   Log-likelihood                    1036.0
Cov. Estimator:            Clustered
                                       F-statistic:                      2.4904
Entities:                         29   P-value                           0.0218
Avg Obs:                      22.207   Distribution:                   F(6,608)
Min Obs:                      16.000
Max Obs:                      24.000   F-statistic (robust):             5.7286
                                       P-value                           0.0000
Time periods:                      2   Distribution:                   F(6,608)
Avg Obs:                      322.00
Min Obs:                      318.00
Max Obs:                      326.00

                                  Parameter Estimates
========================================================================================
                      Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
----------------------------------------------------------------------------------------
IA_Adoption              0.0971     0.2785     0.3485     0.7276     -0.4499      0.6441
Mean_RTI                 0.0331     0.0125     2.6573     0.0081      0.0086      0.0576
GDPCap                9.259e-08  5.547e-07     0.1669     0.8675  -9.967e-07   1.182e-06
Educ_Rate               -0.0064     0.0498    -0.1290     0.8974     -0.1041      0.0913
Unemp_Rate               0.0845     0.0788     1.0719     0.2842     -0.0703      0.2393
IA_Adoption:Mean_RTI     0.1467     0.3867     0.3793     0.7046     -0.6127      0.9061
========================================================================================

F-test for Poolability: 0.3156
P-value: 0.9998
Distribution: F(29,608)

Included effects: Entity, Time
```

Table A4. Complete results of the model by sub-tasks (panel data).

PanelOLS Estimation Summary

Dep. Variable:	Share_Sector	R-squared:	0.2036
Estimator:	PanelOLS	R-squared (Between):	-30.672
No. Observations:	644	R-squared (Within):	0.2008
Date:	Fri, May 23 2025	R-squared (Overall):	-17.849
Time:	19:59:16	Log-likelihood	1101.5
Cov. Estimator:	Clustered		
		F-statistic:	12.827
Entities:	29	P-value	0.0000
Avg Obs:	22.207	Distribution:	F(12,602)
Min Obs:	16.000		
Max Obs:	24.000	F-statistic (robust):	21.181
		P-value	0.0000
Time periods:	2	Distribution:	F(12,602)
Avg Obs:	322.00		
Min Obs:	318.00		
Max Obs:	326.00		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
IA_Adoption	-1.5088	0.9563	-1.5777	0.1152	-3.3870	0.3693
NRA	0.1630	0.0567	2.8727	0.0042	0.0516	0.2744
NRI	0.7514	0.2306	3.2586	0.0012	0.2986	1.2043
RM	0.5949	0.1597	3.7250	0.0002	0.2812	0.9085
NRM	0.3237	0.0468	6.9092	0.0000	0.2317	0.4157
GDPCap	-5.481e-07	1.311e-06	-0.4180	0.6761	-3.123e-06	2.027e-06
Educ_Rate	0.1303	0.0681	1.9122	0.0563	-0.0035	0.2642
Unemp_Rate	0.1239	0.1167	1.0616	0.2888	-0.1053	0.3531
IA_Adoption:NRA	-1.2431	1.4655	-0.8483	0.3966	-4.1213	1.6350
IA_Adoption:NRI	6.3001	4.4038	1.4306	0.1531	-2.3486	14.949
IA_Adoption:RM	7.6221	3.7066	2.0564	0.0402	0.3427	14.902
IA_Adoption:NRM	0.2166	0.6198	0.3494	0.7269	-1.0007	1.4339

F-test for Poolability: 0.6749
P-value: 0.9023
Distribution: F(29,602)

Included effects: Entity, Time

Table A5. ISCO-08 classification: major groups (OC1-OC9).

ISCO-08	MAJOR-GROUP
OC1	Directors and managers
OC2	Scientific and intellectual professionals
OC3	Mid-level technicians and professionals
OC4	Administrative Support Staff
OC5	Service workers and vendors in shops and markets
OC6	Farmers and skilled agricultural, forestry and fishing workers
OC7	Journeymen, operators and craftsmen in mechanical arts and other trades
OC8	Plant and machine operators and assemblers
OC9	Elementary occupations

Source: ILO, International Standard Classification of Occupations 2008 *(ISCO-08)*

Table A6. AI adoption indicators: Eurostat codes and description.

ExpIndicator	ExpIndicatorCaption
E_DI3_HI_AI_TANY:	Enterprises with a high digital intensity index that use any artificial intelligence (AI) technology.
E_DI3_LO_AI_TANY:	Enterprises with a low digital intensity index that use any artificial intelligence (AI) technology.
E_DI3_VHI_AI_TANY:	Enterprises with a very high digital intensity index that use any artificial intelligence (AI) technology.
E_DI3_VLO_AI_TANY:	Enterprises with a very low digital intensity index that use any artificial intelligence (AI) technology.
E_DI4_HI_AI_TANY:	Enterprises with a high digital intensity index (Version 4) that use any artificial intelligence (AI) technology.
E_DI4_LO_AI_TANY:	Enterprises with a low digital intensity index (Version 4) that use any artificial intelligence (AI) technology.
E_DI4_VHI_AI_TANY:	Enterprises with a very high digital intensity index (Version 4) that use any artificial intelligence (AI) technology.
E_DI4_VLO_AI_TANY:	Enterprises with a very low digital intensity index (Version 4) that use any artificial intelligence (AI) technology.

Source: Authors' elaboration based on Eurostat, Digital Economy and Society Survey 2024

Table A7. Proportions of ISCO-08 occupational groups (OC1-OC9) by NACE sector, 2023-2024.

ISCO_08 NACE	OC1	OC2	OC3	OC4	OC5	OC6	OC7	OC8	OC9	Total
C	0.06	0.15	0.14	0.07	0.03	0.00	0.28	0.21	0.07	1.0
D	0.03	0.30	0.31	0.11	0.01	0.00	0.21	0.02	0.01	1.0
E	0.02	0.07	0.17	0.09	0.01	0.00	0.10	0.22	0.32	1.0
F	0.06	0.06	0.10	0.04	0.00	0.00	0.56	0.07	0.09	1.0
G	0.08	0.09	0.12	0.09	0.43	0.00	0.10	0.03	0.06	1.0
H	0.05	0.06	0.10	0.19	0.04	0.00	0.03	0.44	0.08	1.0
I	0.09	0.01	0.05	0.06	0.57	0.00	0.01	0.01	0.20	1.0
J	0.08	0.63	0.19	0.06	0.01	0.00	0.02	0.00	0.00	1.0
L	0.08	0.06	0.61	0.10	0.07	0.00	0.02	0.00	0.06	1.0
M	0.07	0.58	0.22	0.09	0.01	0.00	0.02	0.00	0.01	1.0
N	0.05	0.08	0.10	0.13	0.23	0.03	0.03	0.03	0.32	1.0
S	0.04	0.15	0.10	0.05	0.53	0.00	0.06	0.02	0.04	1.0

Source: Authors' elaboration based on Eurostat – EU-LFS, 2023-2024.

Table A8. Total effects of AI adoption on employment share by NACE sector (2023-2024 panel).

	Efecto Total	Error estándar	t	p-value
C	-0.497413	0.407065	-1.221948	0.221727
D	-0.010643	0.016146	-0.659189	0.509775
E	0.009163	0.065527	0.139841	0.888786
F	-0.389149	0.229912	-1.692601	0.090532
G	-0.443062	0.212104	-2.088896	0.036717
H	-0.294548	0.130074	-2.264469	0.023545
I	0.167546	0.160355	1.044846	0.296094
J	0.097501	0.042451	2.296792	0.021631
L	0.142658	0.065834	2.166947	0.030239
N	0.188873	0.080707	2.340230	0.019272
S	0.071332	0.024619	2.897401	0.003763

Source: Authors' elaboration based on Eurostat (Digital Economy and Society Survey; EU-LFS), 2023-2024.

Table A9. Total effects of AI adoption on employment share by occupation ISCO-08 (panel 2023-2024).

ISCO	Efecto Total	Error estándar	t	p-value
OC0	-0.000067	0.000541	-0.124804	9.006790e-01
OC1	0.040317	0.053020	0.760409	4.470099e-01
OC2	3.706992	0.305779	12.123127	0.000000e+00
OC3	0.490175	0.142945	3.429129	6.055207e-04
OC4	-0.099665	0.079349	-1.256034	2.091035e-01
OC5	-1.325858	0.185349	-7.153318	8.471002e-13
OC6	0.000644	0.010626	0.060576	9.516969e-01
OC7	-1.014896	0.188188	-5.392982	6.929785e-08
OC8	-0.932223	0.100642	-9.262771	0.000000e+00
OC9	-0.865419	0.088340	-9.796409	0.000000e+00

Source: Authors' elaboration based on Eurostat (Digital Economy and Society Survey; EU-LFS), 2023-2024.

Table A10. Total Effects: AI Adoption and Sector Employment Share by Task Category (NRA, NRI, RC, RM, NRM), 2023-2024

	Efecto_total	SE	t	p-value
RC	−1.5088	0.9563	−1.5777	0.1146
NRA	−2.7520	2.0720	−1.3282	0.1841
NRI	4.7913	3.5896	1.3348	0.1820
RM	6.1133	2.8184	2.1691	0.0301
NRM	−1.2922	0.8511	−1.5183	0.1289

Source: Authors' elaboration with data from Eurostat – Digital Economy and Society Survey and EU-LFS, 2023-2024; sub-tasks defined according to Mihaylov and Tijdens (2019).

Classification of tasks based on Mihaylov and Tijdens (2019): NRA (non-routine analytics), NRI (non-routine interactive), CR (routine cognitive), MR (routine manuals) and NRM (non-routine manuals).

Table A11. Variance Inflation Factors (VIF) of the sectoral model, panel 2023-2024

	Variable	VIF
0	const	81.995129
1	IA_Adoption	14.740148
2	GDPCap	2.128643
3	Educ_Rate	1.792428
4	Unemp_Rate	1.142535
5	NACE_C	8.326376
6	NACE_D	5.631709
7	NACE_E	5.524543
8	NACE_F	6.992427
9	NACE_G	7.899199
10	NACE_H	7.715439
11	NACE_I	6.991144
12	NACE_J	10.252530
13	NACE_L	6.551559
14	NACE_N	7.917726
15	NACE_S	4.908736
16	NACE_C_IA	5.570891
17	NACE_D_IA	6.566965
18	NACE_E_IA	2.656118
19	NACE_F_IA	2.781183
20	NACE_G_IA	4.240057
21	NACE_H_IA	3.666605
22	NACE_I_IA	3.044826
23	NACE_J_IA	16.152085
24	NACE_L_IA	3.131546
25	NACE_N_IA	4.844024
26	NACE_S_IA	3.071753

Source: Authors' elaboration based on the sectoral estimate (Eurostat data – Digital Economy and Society Survey & EU-LFS, 2023-2024).

Table A12. Variance Inflation Factors (VIF) of the occupational model, panel 2023-2024

	Variable	VIF
0	const	46.564962
1	IA_Adoption	10.102559
2	GDPCap	1.853157
3	Educ_Rate	1.768007
4	Unemp_Rate	1.128229
5	ISCO_OC0	3.631463
6	ISCO_OC1	3.631463
7	ISCO_OC3	3.631463
8	ISCO_OC4	3.631463
9	ISCO_OC5	3.631463
10	ISCO_OC6	3.631463
11	ISCO_OC7	3.631463
12	ISCO_OC8	3.631463
13	ISCO_OC9	3.631463
14	ISCO_OC0_IA	3.831463
15	ISCO_OC1_IA	3.831463
16	ISCO_OC3_IA	3.831463
17	ISCO_OC4_IA	3.831463
18	ISCO_OC5_IA	3.831463
19	ISCO_OC6_IA	3.831463
20	ISCO_OC7_IA	3.831463
21	ISCO_OC8_IA	3.831463
22	ISCO_OC9_IA	3.831463

Source: Authors' elaboration based on occupational estimation (Eurostat data – Digital Economy and Society Survey & EU-LFS, 2023-2024).

Table A13. Breusch heteroskedasticity test – Paid by type of panel (sector and occupational)

Panel	BP Statistician	P-Value
Sector	215.108	0,000
Occupational	731.838	0,000

Source: Authors' elaboration with data from Eurostat – Digital Economy and Society Survey and EU-LFS, 2023-2024.

Table A14. Number of observations by country on the panel (2023-2024)

	Country	Observations
0	Sweden	24
1	Netherlands	24
2	Poland	24
3	Portugal	24
4	Belgium	24
5	Romania	24
6	Hungary	24
7	Greece	24
8	France	24
9	Serbia	24
10	Slovakia	24
11	Denmark	24
12	Czechia	24
13	Slovenia	24
14	Bulgaria	24
15	Germany	23
16	Croatia	23
17	Norway	22
18	Austria	22
19	Cyprus	22
20	Lithuania	21
21	Latvia	21
22	Ireland	20
23	Estonia	20
24	Spain	20
25	Malta	18
26	Finland	18
27	Italy	18
28	Luxembourg	16

Source: Authors' elaboration based on Eurostat – Digital Economy and Society Survey and EU-LFS

Table A15. NACE Rev. 2 classification to 1 digit.

SECTION (1 digit)	Description (official title abbreviated in Spanish)
A	Agriculture, forestry and fisheries
B	Extractive industries
C	Manufacturing industry
D	Supply of electricity, gas, steam and air conditioning
E	Water supply; sanitation, waste management and decontamination activities
F	Construction
G	Wholesale and retail trade; Motor vehicle and motorcycle repair
H	Transport and storage
I	Hospitality (accommodation and food and beverage services)
J	Information and communications
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative activities and ancillary services
O	Public administration and defense; Compulsory social security
P	Education
Q	Health and social service activities
R	Artistic, recreational, and entertainment activities
S	Other Personal Services
T	Activities of households as employers; production of goods and services for own use
U	Activities of offshore organizations and bodies